UCL (University College London)

URBAN DESIGN AND DRUG CRIME:

UNCOVERING THE SPATIAL LOGIC OF DRUG CRIME IN RELATION TO THE URBAN STREET NETWORK AND LAND USE MOSAIC IN LONDON

by

Lusine Tarkhanyan

The thesis is submitted for PhD degree

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‘ I, Lusine Tarkhanyan confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.'

Abstract

This multidisciplinary research is concerned with the ways in which the morphology of the urban landscape may affect the spatial distribution of drug crime incidents. Following from this rationale, the research pursued the following three objectives.

First, the research explored where drug dealers are known to sell drugs, and the extent to which and in what ways these places differ from those places that they do not. In particular, the research focused on examining whether the types of places at which drugs are sold have the street network characteristics of places that offer good retail potential. Employing space syntax technique and event count regression models, the analysis showed that street permeability and proximity to high street significantly increase the likelihood of drug crime.

Second, the research examined drug crime in relation to legal facilities, which inherently and routinely generate large flows of people. Using network distance buffers, the criminogenic fields of the facilities were identified. The regression results showed that not only the facility itself attracts crime, but the facility's specific configurational positioning on the street network also influences the likelihood of crime.

The last part of the research examined the relative positioning of drug dealing locations in the city with reference to the level of permeability, the drug types and quantities being sold per street segments. The results showed a spatial differentiation amongst varying drug types according to their drug classes.

The overall picture suggested that the urban fabric, particularly the characteristics of the street network configuration and the way land uses are distributed across the street network, have a great effect on drug occurrences.

This research is dedicated to my grandfather, a great master of his craft and my first teacher of architecture.

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Glossary

Configuration	A spatial relationship between – e.g. streets that takes into account their relationship to other streets (Hillier 2007)
Configurational analysis	Relational analysis of the street network pattern of connections, where the geometrical and topological properties of street network layout are taken into account
Connectivity	An index that shows how many streets the given street segment is directly connected to
Criminogenic	Refers to an effect of legal activity that causes a criminal event
Drug dealing	The same as drug supply, refers to supplying or offering to supply an illicit drug(s) for money
Drug market	Refers to the publicly accessible urban location(s) where illicit drugs are illegally traded
Drug possession	Possession of illicit drug(s) with intention to supply
Drug production	Production or distribution of large quantities of illicit drug(s)
Euclidean distance	The measure of shortest distance between two locations with no constraint on physical environment
Local and regional scale	A measure of scale that accounts for the movement in the city. Local scale refers to movement within the neighbourhood and regional scale refers to movement across the city
Network distance	A measure of distance that is constrained by street network, where the shortest distance between two locations is measured along the street layout
Permeability (or accessibility)	The degree to which both street network layout and urban form facilitates the access to a selected destination
Situational	Refers to the location and time of the crime and the particular nature of the crime target

Through-movement permeability (or choice)	The measure captures the probable amount of movement passing through each segment in the network within a given distance (sometimes termed 'radius').
To-movement permeability (or integration)	The measure captures the locations that are more frequently and with less effort able to be reach from all other segments within a given distance (sometimes termed 'radius').
Topological position	Refers to positioning of the street segment in relation to the entire street network
Topological properties	Spatial measurements of street segments in relation to the shortest paths passing through the network.
Topology	Refers to a pattern of street connections
Visual field	Lengths of road with uninterrupted lines of sight

CHAPTER 1

Introduction

Introduction

"*A key priority for policy should be to improve the knowledge base and understanding of how different drug markets, distribution and trafficking networks develop and operate. This includes accurately mapping local markets and measuring intervention effects*".

(McSweeney *et al.* 2008; p.15 - UK Drug Policy Commission)

Employing a multidisciplinary approach, the research presented in this thesis speaks to some of the above issues. In particular, it draws on theory and techniques from the fields of architecture and environmental criminology to inform understanding of *street level illegal drug markets.* It focuses on the geographical nature and extent of drug markets in the urban street network environment. Moreover, the aim is to examine the extent to which drug crime is related to or spatially embedded within the spatial distribution of legal businesses and land uses in the city.

1.1 The cost of urban crime

Crime is defined as 'an action or omission which constitutes an offence and is punishable by law' (Oxford English Dictionary, 2009). The reasons for crime are complex and involve many social, environmental, housing, employment and other factors that influence the likelihood of someone engaging in crime (Burgess 1916; Shaw and McKay 1969; Jacobs 1961). The geography of crime is not random (Sherman et al. 1989; Weisburd et al. 2004; Johnson 2010) and it is very much dependent on the situational opportunities present in the environment (Felson and Clarke 1998). For instance, it was found (Guerry 1833; Quetelet 1835; Glyde 1856) that burglaries are more likely to occur in affluent urban neighbourhoods, than poor rural areas; however serious crime, such as murder or rape is more likely to happen in rural poor areas. Moreover, it was shown (Burgess 1916) that the location of the crime is more important than the social background. It was highlighted (Burgess 1916) that poor housing conditions and proximity to city centre facilitate juvenile crime. Modern urban landscape where a great number and variety of people live in densely populated areas provides many opportunities for the motivated offender. These areas facilitate a large number of potential crime targets in the form of valuable goods, capital and people moving around in the city (Cohen and Felson 1979; Clarke 1999). In comparison to rural environments, urban dwellers have greater mobility to travel over considerable distances and greater anonymity from illegal actions due to a large number of people residing in cities (Cohen and Felson 1979). Although cities facilitate a large number of potential criminogenic opportunities, different types of criminal activities use different situational opportunities (Cornish and Clarke 1986). To burgle a house will require different situational factors than to rob a person or steal from a car. As Johnson and colleagues (2014; p.3) summarise:

> Consciously or otherwise, offenders make a number of choices both when preparing for and when committing crime. The crime has to take place at a particular location, at a particular time, using specific tools (where appropriate), against a specific target, and with a desired outcome of a particular type.

Thus, in a particular situation a potential offender will estimate associated risks and benefits involved in committing particular type of crime. Consequently, this research focuses only on one type of crime - drug crime; it examines spatial situational opportunities that may facilitate this type of crime.

Illicit drugs are associated with crime in many ways. According to the Misuse of Drugs Act 1971, heroin, cocaine, crack, LSD, cannabis, amphetamines and ecstasy are classified as illegal drugs. It is a crime to produce, traffic, supply and possess these drugs. Some researchers (Bennett and Sibbitt, 2000; Chaiken and Chaiken 1990; Parker and Newcombe 1987) have also suggested that illegal drugs – or an offender's dependency on them – may cause other types of crime, such as robbery, burglary, violent crime and more. Others (MacCoun et al. 2003; Hammersley et al. 1989) have argued that there is little evidence of direct link that drug use enables someone to commit a crime. The drug use and crime nexus is very multisided and it involves both as many associations, as variations (Hughes et al. 2014; Bean 2014).

Drug crime has extensive social, economic and health consequences for the society. For instance, drug dealing is believed (Hales et al. 2006) to be a key factor that influenced the growth of gun crime in UK in recent years. Illegal drug dealing negatively affects local communities: it undermines social organisation of the community and neighbourhood reputation (Wilson et al. 2002). For example, local communities affected by drug markets report great fear of crime (Cyster and Rowe 2006).

Overall, the rapid urbanisation of cities, social transformations, economic and scientific developments, the advancement of network infrastructure and vast housing developments, may all have indirectly facilitated the amplified level of crime and the increased cost of crime to society (Cohen and Felson 1979). A recent government report (Brand and Price 2000) highlights that in UK cities alone, the total cost of crime for the year 1999/2000 was £60 billion. This figure includes the cost of valuable goods and property stolen, and the expenditure of the police, security and criminal justice system. The figure does not, however, include the social costs of crime, such as the fear of crime and the impact of crime on residents' quality of life. Of these costs, 1.2 billion is associated with drug offences and almost half of this cost (£516 million) is directly associated with those police activities that are intended to detect and prevent drug crime. However, this does not include the cost of those drug-related offences that may be committed to fund drug purchase.

1.2 A definition of drug markets

The structure of illegal drug markets is defined as "pyramidal and multilevel drug distribution networks" (McSweeney et al. 2008). International trafficking and local street level retail form the top and bottom levels, and the middle level market facilitates large quantities of smuggled drugs to be distributed nationally and regionally (McSweeney et al. 2008). During 2003/04 the size of the illicit drug market was estimated to be £4-£6.6 billion in the UK (Matrix Knowledge Group 2007). According to the Home Office there were approximately 300 major importers, 3000 wholesalers and 70,000 street dealers in the UK (Matrix Knowledge Group 2007).

Law enforcement strategies (ACPO 1985) tend to concentrate on the two top levels of the distribution network, since the detection of the middle-level is very difficult. This is due to it being an established closed, global social network of trusted participants with low frequencies of transactions (Matrix Knowledge Group 2007). Many strategies intended to prevent international drug trafficking involve international multi-agent partnerships between various agencies. Most tactics involve the analysis of intelligence regarding drug syndicate social networks and employ illegal drug detection technologies at border crossings to intercept consignments of drugs (ACMD 1994). It remains very hard to identify and prevent the smuggling of drugs into the country, and despite substantial drug confiscations and arrests, drug markets remain extremely resilient and adaptable both at the regional and international retail levels (UNODC 2012).

At the street market level, the detection of offending is somewhat less complicated. This is because transactions are place-specific, and there are more interactions between strangers (buyers and dealers). Thus, at this level of offending, various undercover police tactics can be used – random patrols, stop and search, test purchase (undercover officer buys drugs from a dealer), reverse sting (undercover officer pretends to be a dealer) (Bean 2014). However, recent reviews (Haracopos and Hough 2005; Mazerolle et al. 2006) indicate that law enforcement only methods appear to be less effective than geographically targeted policing interventions that are partnered with communities and are aimed at drug hot spot areas (Weisburd and Eck 2004). Moreover, scholars (McSweeney et al. 2008; Eck and Wartell 1996) suggest that the most effective strategies for stopping drug dealing from residential and commercial properties involve multi-agency stakeholders with an emphasis on improving the place management and built environment. Since street markets are place specific and – in the context of the drug supply chain - involve the highest number of dealers, scholars (Weisburd and Eck 2004) recommend strategies that focus more on targeting specific places than individual dealers or gangs.

Regardless of the size of the drug market, illegal drugs are bought and sold in the similar way as all other legal goods, thus basic economic laws of supply and demand are in place, where accessibility to potential customers is one of the key factors of successful retail (Eck 1994; Rengert et al. 2000). However, drug dealing is also associated with a high degree of risks involved – legal penalties, theft and violence from competitors are common (Eck 1994). It has been proposed (Eck 1994) that these two aspects contribute to different geographical models of drug markets.

The drug markets are classified as *open*, *semi-open, closed* and *social network* (Eck 1994; McSweeney et al. 2008). Depending on where users and dealers live relative to the market the open drug markets are classified as *local, export, import and public markets* (Reuter and MacCoun 1993). Local or neighbourhood markets are described as places in which both customers and dealers are from the vicinity: they might be neighbours or know each other through other means. When the customers or the users visit the area with the purpose to buy a drug, these markets refer as export markets, since the drug dealers who reside in the neighbourhood sell the commodities to the outside world. Import markets refer to those, where the drug dealer is outsider to the neighbourhood and it sells the drug to the neighbourhood users. In public markets, the drug exchange takes place at public locations and along permeable streets (Eck 1994) that are routinely used by a large number of non-residents. These markets are large enough to support several competing drug dealers and can secure a high frequency of transactions.

Semi-open markets are typically established when both participants (dealer and buyer) aim to lessen the risks associated with open street markets. For such markets, the dealers and buyers do not usually live in the same area. In UK semi-open markets refer to clubs and drinking establishments, where the transactions happens on the basis that customer looks like a drug user.

Closed markets are formed from a network of friends and other trusted people. Their locations are determined by both participants of the transaction and are distributed over a wide area. This type of market is the norm in wholesale drug dealing.

Technological advances and the widespread availability of postal services have contributed to the establishment of web-based drug markets, where participants have high anonymity. For such markets, trading can be conducted using digital crypto currency and the drug may be delivered via post (Martin 2013; Barratt et al. 2014). This is new and innovative way of drug dealing, where the entire world is a potential marketplace hidden from law enforcement authorities. Recent research (Aldridge and Décary-Hétu 2014) suggests that with this type of drug market, large quantities of drugs are purchased for resale; that is, to street drug dealers buying stock to sell offline.

Despite the new forms of drug markets, at the street level, drug dealing can be very lucrative business. Report (Reuter & Greenfield 2001) suggests that the value of heroin per kg is 30 times more than gold. The reason for this is that because of legal restrictions the demand is higher than the available supply. As a result, the street retail price differs drastically from the production cost. To illustrate, research suggests (Matrix Knowledge Group 2007) that the price of producing cocaine on a farm costs £350 per kilo, however, when it reaches the potential users, the street price is £51,659 per kilo. For heroin, the production costs is around £450 per kilo but the street price is about £75,750 per kilo (Wilson and Stevens 2004). More recent retail prices for different types of drugs in the UK are not available, however, it is believed (IDMU Drugs Survey 2010) that there has been a dramatic increase up to 50% in prices since 2010, especially for cocaine and cannabis.

1.3 Street drug dealing

Relative to other types of drug market, street level markets have several inherent characteristics that may make their policing easier. For example, compare them to drug markets that are formed through social networks. For such markets drug dealing can happen anywhere in the city, as long as a drug dealer and a buyer can locate each other. In contrast, open street markets are strongly connected to places, as dealers will sell from static sites, so customers know where to find them. Moreover, research suggests that a high frequency of transactions cluster at the specific types of places that may be conducive to drug dealing, such as those locations that are near to major thoroughfares or arterial routes (Eck 1994). These places are attractive because they usually have a high number of potential buyers passing by. Furthermore, it is suggested (Rengert et al. 2000) that in order to stay profitable, drug market locations should be attractive enough to a sufficient number of drug users. The attractiveness of the place is partially determined by the surrounding facilities (retail outlets, cash facilitating land-uses, recreational facilities, drinking outlets), but above all by how far a buyer is prepared to travel to make a purchase. For example, in his ethnographic research of drug users travel patterns Pettiway (1995) discovered that they would not normally travel more than one-mile to purchase a drug. Finally, in the case of successful police operations, research suggests that the spatial displacement of a market, if this occurs, will most likely be limited to the nearby locations. For example, Weisburd and Green (1994) found that despite high detection risks, dealers preferred to stay in an area that was already known as a drug marketplace and that has been proven to be accessible to new customers.

In spite of the issues discussed above, at the street level, the impact on drug crime of police enforcement strategies has been inconsistent (Aitken et al. 2002; Webster et al. 2001; Wood et al. 2004; Weisburd and Green 1994, Home Office News and Publications 2005). It is suggested (Bean 2014) that proactive policing – a test purchase strategy is more successful than reactive policing, such as stop and search strategies. However, the police strategies that are aimed at drug crime hot spots and involve both local agencies and communities have proven to be most successful so far (Weisburd and Green 1994; Home Office 2005 – Operation Crackdown; Bean 2014 – Kings Cross project).

It is also suggested (Weisburd and Eck 1994; Bean 2014) that since the demand for drugs displays a non-random spatial pattern across the urban environment, crime prevention strategies might usefully focus on targeting and altering specific locations that are conducive to drug crime, rather than or as well as, focusing on particular individuals or groups of people. It has been proposed (Rengert 1996) that the results are inconsistent, as the different forms that retail sales at the street-level can take in different places have not been explicitly considered. Therefore, a thorough knowledge of the drug marketplace should precede any interventions (Jacobson 1999), including an investigation of the built environment features present in the area to determine why particular street segments are attractive for drug dealing in the first instance. Eck (1995) argues that since the key balance between access and security affects the geographical models of drug markets, studying geographical patterns of those markets can give a valuable insight into the typology of those markets for future law enforcement intervention practices. For instance, from the detection and prevention perspective it is quite useful to know firstly, on which type of street segment police need to concentrate their resources, and secondly, which are the segments that have a high probability of being or becoming drug dealing places.

1.4 The research questions

Although, many types of crime might be driven by, or indirectly related to the purchase or use of drugs, this research examines only those offences that are directly related to illegal drugs. As specified by UK law these are drug production, drug supply and drug possession crimes.

In particular, this research is concerned with the location of drug markets at the street segment level and whether their placement can be understood by studying the design of the urban environment in a novel way. Specifically, this research investigates the extent to which illicit drug markets depend on the particular geography of places and on their amenities, and how the areas surrounding drug marketplaces affect their suitability as drug markets and what makes them attractive from an economic perspective. Since the main purpose of illicit drug markets is to provide and secure the supply-chain of illicit commodities, the understanding of *how* and *where* buyers and dealers position themselves to engage in transactions is critical to crime prevention. Following from this rationale, the aim of the research is to pursue three main objectives:

Firstly, if it is reasonable to consider the urban street network as a primary determinant of human mobility dynamics, which brings potential sellers and customers together, then understanding the extent to which street drug markets depend on both the spatial properties of street layout and on the movement of people is important. This part of the research aims to explore where drug dealers are known to sell drugs, and the extent to which and in what ways these places differ from those places where they do not. In particular, informed by theories of environmental criminology (see Chapter 2), the aim is to examine whether the types of places at which drugs are sold have the sorts of topological or street network characteristics of places, which offer good retail potential. It is not suggested that drug dealers might engage in such analysis themselves when deciding where to sell drugs, but they may be able to identify such places intuitively. Regardless, the question is an empirical one that might inform police practice and academic research alike. For example, the research may enable us to predict the likely locations of existing, but currently undiscovered drug markets based on the characteristics of the street network (and other spatial factors).

Secondly, it is proposed that the location of drug markets might be influenced by the availability of, and proximity to specific legal land uses that attract or are used by a large number of people, such as transport infrastructure, entertainment districts and cash facilitating businesses. It is suggested that there will be more chance of encountering potential drug users near these types of land uses and activities, than elsewhere in the neighbourhood. Thus, the research will examine if there is a criminogenic influence of legal land uses on drug crime placement and, if so, how strong this effect is.

Thirdly, the research will examine if different types of drug marketplaces can be identified in the city based on principles from a spatial economics perspective. For instance, in the case of the legal goods market, highly valuable goods are usually purchased by people infrequently, but retailers are usually to be found in very permeable urban locations that attract many potential customers from remote locations. Conversely, local markets tend to supply daily items, which consumers wish to purchase within a short travelling distance. Following from this logic, a final aim of the research is to study patterns of drug dealing incidents in terms of how they vary depending on the type and variety of drugs being sold per street segment and whether it is possible to identify local and regional drug markets.

1.5 Case study and research data

Data concerning incidents of drug crime were provided by the London Metropolitan Police for the period 2009-2011 for the London borough of Tower Hamlets. For the two-year time period, there were 9,318 cases of drug selling activities recorded. These were identified from normal police practice and from four police operations that targeted two council estates in the borough. It should be noted that, since drug offences are essentially victimless crimes, they are identified through police action. Consequently, it is possible that the spatial pattern of detected crimes may be associated with police patrolling patterns or police experience of identifying drug dealing. Thus, as there is no 'victim' reporting offences, street segments with no crime may not indicate a lack of crime, but a lack of police patrols to spot drug transactions. The extent to which this is the case is unknown. The reader should be aware of this issue when interpreting the findings presented in this thesis. However, two additional points are important to make. First, this caveat applies to most existing studies of drug crime and similar offences. And, second, in what follows spatial patterns are explored for three different types of offences, for which different patterns are anticipated (see Chapters 4; 5 and 6). If it were the case that police patrol routes explained the spatial pattern of drug crime, then differences in the patterns observed across offences would not be expected to align with a-priori expectations.

Apart from the police data, a range of other data is used in this research. These include geographic maps of all existing street segments and pedestrian paths of the borough, and land-use information regarding all existing residential and commercial premises. In conjunction with the police data this allows the construction of a database where every given street segment had information on land-use type and whether or not drug dealing incidents had occurred on it. The grouping of these data at the street segment level allows the testing of hypotheses that will be discussed in subsequent chapters.

1.6 A synopsis of the research methods

This research follows a case-study design, where the crime data are examined in depth in relation to various properties of the urban street network. Quantitative data analysis, employing a unique combination of methodological approaches from the fields of both criminology and architecture, will be presented.

In order to quantify and examine systematically the potential differences in locations where drug dealing do and do not occur, the research will employ a relatively novel suite of analytic techniques developed in the discipline of architecture collectively known as 'space syntax' (Hillier and Hanson 1984). The approach allows the questions posed above to be examined in a completely different manner to more traditional geographical and hot spot methods. The latter (usually) ignore the street network and how its topology – both at the local and citywide scale – might affect human behaviour and mobility. In contrast, Space syntax does exactly this. Because the morphology of the street network shapes the way people navigate space, space syntax sees the urban grid as fundamental in shaping the location of different social interactions and human activities across space. In particular, the techniques estimate the extent to which a particular layout is likely to increase the potential for the movement of people to and through a specific space, and the likely land use activities in that locale. Thus, the approach is powerful enough to study problems either at the localised street segment level, at the scale of the whole city, or anything in between. Additionally the techniques allow for the systematic examination and comparison of several locations based on their spatial morphology, the level of permeability, visibility and connectivity. Thus, it is possible to identify the spatial differences between locations from a topological perspective. This is valuable for examining the characteristics of drug dealing locations.

When examining patterns of crime in the urban environment, the spatial dimension of the data should be explicitly acknowledged. For example, places that are near to each other can influence each other or are likely to share similar characteristics than places that are far apart (Tobler 1970; Miller 2004). This creates a form of dependency in the data that – to avoid errors of statistical inference – should be accounted for in the methodology employed. Standard statistical models such as ordinary least squares regression do not do this, and so spatial statistical models should be (and are) used to diagnose for and account for such effects where they exist. Consideration too should be given to the fact that crimes are rare events and so particular types of statistical model are appropriate for their analysis. For this reason, in this thesis Poisson regression models is used to test hypotheses.

Overall, given the multidisciplinary nature of this research, it enhances the understanding of how drug crime is spatially patterned in the city and to inform theories from both disciplines involved. By combining the theories and methods developed in the field of architecture and criminology, the research aims to contribute to a better understanding of the theories, methods and definitions used in both disciplines thereby establishing closer connections between the disciplines. Moreover, it is hoped that the knowledge generated as part of this research will inform crime detection and prevention strategies. To facilitate this, the research will also be summarised for practitioners in the form of crime briefs and recommendations for police agencies and urban planners correspondingly.

The research aims to contribute to the empirical analysis of crime. Street drug markets have rarely (Friedrich et al. 2009) been examined at the street unit level. Instead, traditional spatial and hot spot methods are generally employed (Rengert et al. 2000; Braga et al. 1999; Weisburd and Green 1995; Green 1995; Weisburd and Mazerolle; 2000), with data aggregated to areal units, which ignore the street network and how its layout might influence human movement and criminal behaviour in the city.

The advantage of using the street segment as the unit of analysis is that it allows the precise quantification and analysis of spatial differences across the street network. For example, the distance between incidents can be measured both metrically, using network distance or topo-metrically (for instance, incidents happened two streets away from the highway). The permeability and accessibility of a street segment can also be meaningfully quantified. This is the first study to undertake research on drug crime at the street segment level of analysis using such approaches. Moreover, within this single study, different definitions and models of distance to measure the street segment permeability are used (detailed in Chapter 5). The research also provides important insights into the nexus of illegal drug dealing and legal land uses. It is the first study that examines spatial patterns of drug crime in relation to street network permeability and different land uses within a single model. This enables the estimation of how strong the criminogenic effect of particular land uses might be, and how far along the street network this influence might spread. Such knowledge might be valuable for the prevention of drug crime and for managers of the corresponding commercial premises (Eck and Wartell 1998; Madensen and Eck 2012).

Therefore, this study makes a major contribution to research into drug crime by demonstrating that by studying urban environment new and multisided insight can be gained into how drug dealing occurs in the city.

1.7 An overview of the dissertation structure

This PhD thesis consists of nine chapters, including this one. The introductory chapter was intended to provide a background to the thesis, to establish the desirability of the research and to detail the main objectives to be accomplished by this study. The second chapter begins with a brief overview of recent theoretical developments in the field of environmental criminology and architecture regarding crime patterns and the urban environment in general. It then provides a comparative analysis of the empirical findings from both disciplines, considering how street network permeability might influence crime. It identifies the main gaps in drug crime knowledge and proposes the rationale for the present study. The third chapter introduces the main case study area and the crime data to be analysed. It identifies an applicable unit of analysis and examines general trends in the crime data. The fourth chapter is concerned with one of the core methodologies used in the research. It introduces the Space Syntax methodology that will be used to try to explain spatial patterns of drug offences in subsequent chapters of the thesis. The main empirical analysis of this research is divided into three separate analytic chapters. Each includes a focused literature review along with methodology, results and conclusion sections. Chapter five examines the design and spatial character of the street network and why this might have an effect on the placement of drug crime in the city. Chapter six analyses patterns of crime in relation to urban land uses and their influence on the positioning of drug crime in nearby areas. Chapter seven examines the placement of drug marketplaces from an economic perspective and suggests a categorisation of drug markets based on their spatial characteristics.

Finally, Chapter eighth draws upon the entire research, reviewing all empirical findings in conjunction with theoretical strands. It highlights the theoretical and methodological implications of the findings for future studies in both disciplines.

CHAPTER 2

State of the art: spatial perspectives on crime

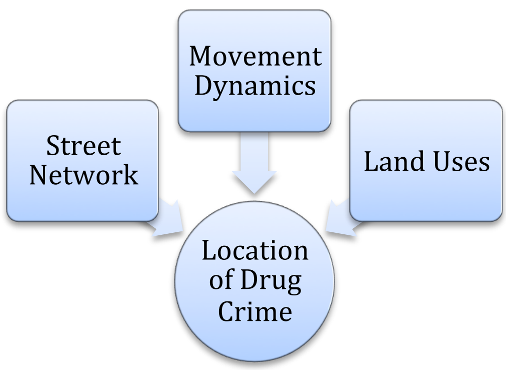
Introduction

Two distinctive groups of theories can be identified that address crime in the city. First are theories that consider the offender's psychological, social and economic motivations that lead to criminal behaviour (Hollin 2013, Andrews 2010; for the in depth discussion see Blackburn 1993). Second are theories of the crime event that focus on situational circumstances where the physical environment, criminogenic opportunities and a lack of social guardianship influence the likelihood of crime occurrence at a particular location and time (Cohen and Felson 1979; Cornish and Clarke 1986). Given that offender motivations are very complex and diverse, scholars (Cohen and Felson 1979) have argued that it is not feasible or helpful to concentrate only on the offender. Moreover, from the perspective of crime prevention and detection, it may be more practical to focus on situational factors that influence the likelihood of crime since these are more amenable to manipulation. This shift from examining offender motivation to criminal events has led scholars to focus on the geographical as well as sociological aspect of crime. For example, since the mid 1980s Environmental Criminology scholars (e.g. Brantingham and Brantingham 1981b; Roncek and Lobosco 1983; Bevon 1984; Felson 1987; Eck and Weisburd 1995, Johnson and Bowers 2007) have paid great attention to *where*, *when* and *how* crime occurs in the city. In particular, researchers studied the impact on crime of an offender's and potential victim's daily movement patterns (Cohen and Felson 1979; Brantingham and Brantingham1993), the spatial characteristics and distribution of crime targets (Brantingham and Brantingham1981b), (Brantingham and Brantingham 1993), the perceptual process that leads to the choice of crime sites (Cohen and Felson 1979; Brantingham and Brantingham 1993), the juxtaposition of land uses and how they influence crime (Brantingham and Brantingham1995); and how the street network system and traffic and pedestrian flows influence crime (Beavon et al. 1994).

Empirically, the analysis of large frequencies of crime facilitated the use of statistical techniques for the purposes of hypothesis testing, and the estimation of the impact on crime of prevention initiatives. However, although scholars have emphasised the influence of the built environment on crime (Jeffery 1971; Newman 1972), and increasingly employ fairly sophisticated spatial econometric statistical models (Bernasco & Block 2011; Bernasco and Elffers 2010; Bernasco; 2010; Levin et al. 2004; Anselin et al. 2000), the types of analyses typically undertaken have been somewhat simplified in the way that they examine the role of urban form and layout.

Around the same time that studies of environmental criminology emerged, a new vision of how cities develop and function was proposed in the field of architecture. Several propositions (Lynch 1960; Steadman 1983; Hillier and Hanson 1983) suggested a shift in the paradigm: from examining the aesthetics of buildings and cities to understanding the deeper structure of the buildings and cities and their social impact on the way the spaces are used in daily life. Scholars (Hillier and Hanson 1983; Hillier 2007) argued that architectural theories were very normative and could be used to generate design, but paid no attention to the configuration of the built environment, where for instance the city can be represented as a 'featureless plain' (for instance, land use distribution model (Alonso 1964) or central place theory (Christaller 1966). Thus, while normative theories could be used to generate designs, "they are too weak in predicting what these designs will be like when built" (Hillier 2007, p. 47) or how it will affect the inhabitants. In the mid 1970s there was a shift in architecture from normative theories that set out the rules of how to design spaces, to analytical theories that aimed to examine how spaces would be used after they had been designed and to understand the regularities of those spaces. The scholars from Configurational Theories of the built environment (Hillier and Hanson 1983) started to examine the underlying processes that shape movement patterns in the city, the distribution of commercial and residential land uses across the street network, the relationship between street permeability and mixed-uses, and the navigation and cognitive aspects of space, including topological and morphological properties of urban spaces. These studies examined many social and economic activities taking place in the city and how urban spaces facilitate or impede these processes. Thus, crime as an urban phenomenon was an important subject of these studies (Hanson and Hillier 1987; Hillier 1991). Several studies (Hillier and Shu 2000; Hillier 2004; Hillier and Sahbaz 2008; Friedrich et al. 2009; Chiaradia 2009) examined different types of crime through the prism of configurational analysis of the built environment. The results from these studies suggested that the way the street network is organised and the way both the movement densities and potential crime targets are distributed across the network have a critical effect on the distribution of crime patterns. Unfortunately, since the scholars were more interested in the urban aspect of the problem, they paid less attention to the appropriateness of the statistical methods applied, and used models that do not account for any spatial dependency in the data. Thus, studies conducted under the rubric of Environmental Criminology have often employed more robust statistical techniques to conduct hypothesis testing, but have used relatively crude characterisations of the urban environment. For studies of Space Syntax, the reverse has frequently been the case. As a result, commonly criminologists (Armitage et al. 2011) can be sceptical about urban studies of street networks and crime.

By combining the strengths of the two approaches, the multidisciplinary strategy proposed in this research aims to provide new insight into the spatial logic of crime and how illegal activities are distributed across the street network in relation to legal land uses and other urban activities. The empirical research presented in this thesis is developed based on a joint approach, where spatial-topological characteristics of the urban environment are examined against the criminological perspective of locational preferences of drug dealing in the city. In particular, patterns of drug crime are examined with respect to three features of the urban environment that potentially influence drug market location choice. These are the *street network*, *movement dynamics* and *land use distribution*. In this study, all three influences are represented and examined statistically.



This chapter is structured as follows: in the first part, perspectives from Environmental Criminology will be introduced. Next, regularities observed by urban studies scholars associated with how people move in the city will be discussed. After this, there will be a discussion of the contribution that can be made by using street network analysis techniques to study crime problems, particularly drug crime. This is followed by a discussion of the role of street network permeability in spatial patterns of crime. The second section introduces the state of the art in drug crime research and what is already known about the locations of drug crime. The final part of this chapter presents the research design of the current study and the primary research objectives.

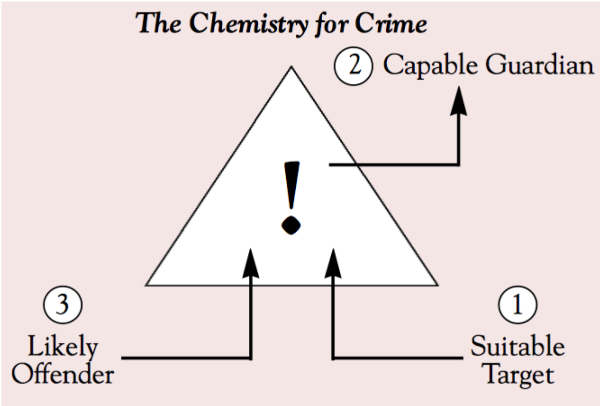
2.1 The Crime And Urban Mosaic

2.1.1 Mechanisms of crime

An urban-dweller's routine consists of a number of activities distributed across the city and the practice of committing crime is no exception. According to theories of Environmental Criminology crime is the product of specific criminogenic opportunities present in the environment (Felson and Clarke 1998). Criminally motivated individuals come to know these opportunities through daily interaction with their surrounding settings. Thus, understanding *when*, *where* and *how* those opportunities affect criminals' choices is central for developing effective crime prevention strategies. Importantly, different crime types are associated with different opportunities present in the environment: robbery on the street from a person has very different criminogenic circumstances than a theft from the car or a burglary from a house. Moreover, those opportunities might have different spatial and temporal distribution in the city, reflecting the differences in daily routine of urban-dwellers moving between work, home and recreation (Cohen and Felson 1979; Brantingham and Brantingham 1984). For instance, the criminal opportunities for robbery on a busy high street at the weekend is different from the opportunities for house burglary in a half vacant residential neighbourhood on a Monday afternoon. Routine Activity and Crime Pattern Theory, to be discussed next, explain how criminogenic opportunities are distributed in the city.

According to *Routine Activity Theory* (Cohen and Felson 1979) in order for a crime to occur three conditions must be satisfied at a given location at a given time: there must be a motivated criminal ready to commit a crime, an available or vulnerable victim or target, and these must converge in the absence of a capable guardian who could otherwise prevent the crime incident; including intimate handlers (Felson 1986) or place managers (Eck 1995) who know potential offenders and have social control or managers who monitor and control commercial premises correspondingly, **Figure 1.**

Figure 1: The crime triangle

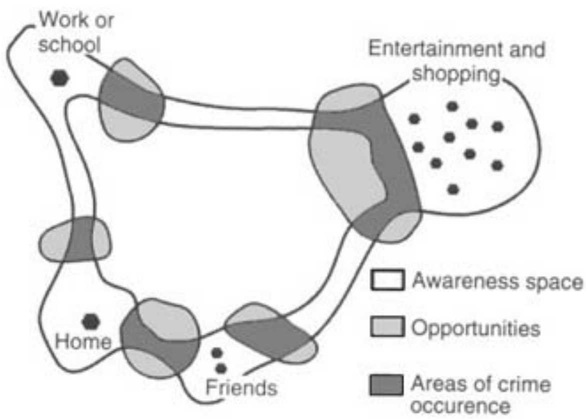


Source: Felson, 1998. Crime and Everyday Life, Second edition. Thousand Oaks, CA: Pine Forge Press.

The approach assumes a motivated criminal as given and highlights that if at least one of the other two elements is absent at a given time and place, the likelihood of crime is reduced. The capable guardian can be an official person, such as a police officer, security personnel, place managers or an informal guardian, such as a passer-by in the vicinity of the target, neighbours, friends, or parents. If at least one effective guardian is present at the location, the likelihood that the motivated criminal will attack the target is considerably reduced. For instance, in the case of drug crime, in order for crime to occur, a motivated drug dealer has to come to the same place as the attractive target – a potential drug buyer. If the guardian is absent, corrupt, or present but not capable of preventing the crime, the drug transaction is likely to occur (Eck 1994; Eck and Weisburd 1995).

Crime Pattern Theory (Brantingham and Brantingham 1981 b; 1993) suggests that criminals identify and select crime targets as a by-product of their routine activities. These activities include travelling from home to places of work, school, recreation and so on. As a result of this activity they develop awareness of these places and those in between. These places and those locations nearby therefore comprise the primary *activity space* that individuals visit over the course of the day. Moreover, for such areas they develop awareness not just of the locations but also of the likely crime opportunities and the benefits and risks associated with exploiting them. Scholars (Felson and Clarke 1998) propose that motivated criminals will go for the easiest crime opportunity and may ignore the "second best", because it might not be worth the effort. The main proposition is that it is easier to commit an opportunistic crime while navigating between the activity spaces, than purposely make a journey to search for opportunities to commit a crime in unknown locations, see **Figure 2**. The theory suggests that crime patterns can be explained by examining both distribution nodes that people visit or inhabit, the pattern of paths that connect those nodes of daily activities and how cognitive representations of space are shaped during the daily routine in the city.

Figure 2: Activity nodes, awareness spaces and crime places



Source: Brantingham and Brantingham (1981b)

Brantingham and Brantingham (1984) distinguish between the *nodes*, *paths* and *edges* that comprise their *activity and awareness spaces*. *Nodes* are those urban activity places, including public spaces, commercial and residential land uses, that both the criminal and the potential victim visit during the day. Crime can happen either at such nodes or nearby. The degree to which these nodes of activity may influence the occurrence of crime depends on the type of activities taking place at them and the particular users that are attracted to that node. For instance, bars and clubs might become places for antisocial behaviour, or alcohol and drug related places of crime. Moreover, the particular juxtaposition of different activity nodes in relation to each other and to the surrounding environment can increase the risk of crime (Brantingham and Brantingham 1975) because they facilitate or attract more potential crime targets to the area.

Paths are the routes that criminals and potential victims navigate to travel between two or more activity nodes during their daily routine, or on special occasions. The choice of route determines the amount of knowledge learnt about the neighbourhoods and the city as a whole. According to the theory, crime is more likely to happen within a certain distance of these places. Thus, the particular choice of paths and the way the paths are distributed in the city influences the likelihood of an offender finding a suitable target or other people being victimised. Overall, frequently used paths are predicted to have more aggregate crime than the routes that are used infrequently (Brantingham and Brantingham 1993; Rengert and Wasilchick 2000).

Edges refer to the physical and notional boundaries between areas where there is a distinctive change in urban form and urban characteristics. For instance, commercial vs. residential areas, rich vs. poor areas, those to be found near transportation hubs or highways; these are the neighbourhoods, where many strangers pass by and the risk of being recognised is low. The theory also suggests that many crimes will occur at locations for which the routine activity of the place has a distinctive temporal edge. For instance, antisocial behaviour may be more likely to occur at a stadium after a sporting event is finished (Kurland et al. 2013).

Changes in daily routine, such as home address, job or school, will consequently shift the distribution of a person's activity spaces and the paths they travel. Shifts in activity patterns might also occur due to modifications in the street network or transportation system. For example, the introduction of road closures may influence the crime opportunity (Bevis and Nutter 1977; Beavon et al. 1994; Clarke 2002).

Thus, the geographical distribution of various legal activities in the city and the way they are connected is seen as an important aspect of crime pattern theory and the associated research (which will be discussed further in Section 2.1.3).

Consequently, it is proposed that incorporating knowledge generated from research conducted in the disciplines of urban studies and architecture regarding the street network and the distribution of land use mosaic, may provide an important step in understanding more about crime patterns and, how appropriate crime prevention strategies might be developed. In the next section, general concepts from urban research studies are presented on the role of the street network in facilitating movement through the city and enabling various activities across the network.

2.1.2 Street movement dynamics and urban mosaic

As discussed, according to theories of Environmental Criminology, the patterning of criminal activities in the city can be understood through the examination of everyday movement to and from activity nodes. Since the route choices between different activity nodes are constrained by the street network, examining the layout of streets and the way activities are distributed across the network in relation to one another may provide valuable insight into the clustering of crime across neighborhoods. According to urban research (Hillier 2007) the greatest interaction and contact in the cities is generated through the street network. This proposition is based on the fact that most urban locations are used for movement between many locations and the street network is a primary facilitator of these dynamics. The Theory of Natural Movement and the Movement Economy Theory seek to explain how street network facilitates movement and distribution of various activities across the city. These two theories will now be discussed.

The principle of natural movement (Hillier et al. 1993) is defined as the relationship between urban configuration and the rate of movement per street segment. Researchers (Hillier et al. 1993) propose that the urban street grid itself is the primary generator of different movement rates across the network. The rate of expected movement for the given street segment is determined by the position of that segment in the configuration of the urban grid and not by the influence of specific land-use attractors. This proposition is in direct contrast to other urban models of movement (*gravity model* (Haynes and Fotheringham;1984), where movement is assumed to be influenced by specific land-use attractors. Here, the degree of land-use attractiveness determines movement volumes to and from given land uses. Thus, according to these models land use attractors are the primary generators of movement in the city. The main difference between these two propositions is that the gravity model assumes that the aggregate movement in the city is generated between pairs of origins and destinations (i.e. from home to shopping centre) and the Natural Movement Theory assumes that movement is generated between all possible locations, where every space in the city can be an origin, a destination and a through movement space. Thus, the aggregate movement per segment is a result of the way streets, alleys, squares, individual spaces and urban features are interlinked in the city.

The Movement Economy Theory (Hillier and Penn 1996, Hillier 1997; Hillier and Vaughan 2007) further proposes that given the strategic *positioning* of a segment in the configuration, it not only determines how much the street segment will be used for movement, but also consequently influences the location of land uses. According to this theory, land uses and especially commercial land uses are positioned to take advantage of strategic locations, and retailers select specific street segments that inherently have a large volume of movement passing by. Well-positioned commercial land uses attract more movement to the given location (Hillier et al. 1993). Thus, it is proposed (Hillier *op cit*) that the distribution of land uses follows movement volumes in the city, where some categories of land uses can be found along lines of high volume movement, but a sharp turn into a different alignment, where the movement volume drops, also shifts the types of land uses attracted to that area (Hillier 1999;Vaughan et al. 2013). A distinctive positioning of certain segments in the grid structure has the potential to attract high density and mix of activities and subsequently influence the whole area to become an attractive centre of activity in the street grid as well (Vaughan et al. 2013).

These propositions from urban research will be discussed in more detail in chapters 4 and 5. In the next section, the potential contributions to criminological understanding when principles of street network analysis are used to study crime problems are discussed.

2.1.3 Examining crime problems through street network analysis

As discussed, the role of street network and particularly the way it is arranged might have a significant effect on the likelihood of crime occurrence. It can be proposed that all three elements of the crime triangle are somewhat related to different *aspects* of urban space, and that tracing more explicitly the actual effect of spatial layout on the likelihood of crime occurrence might offer new insight into the mechanisms of crime.

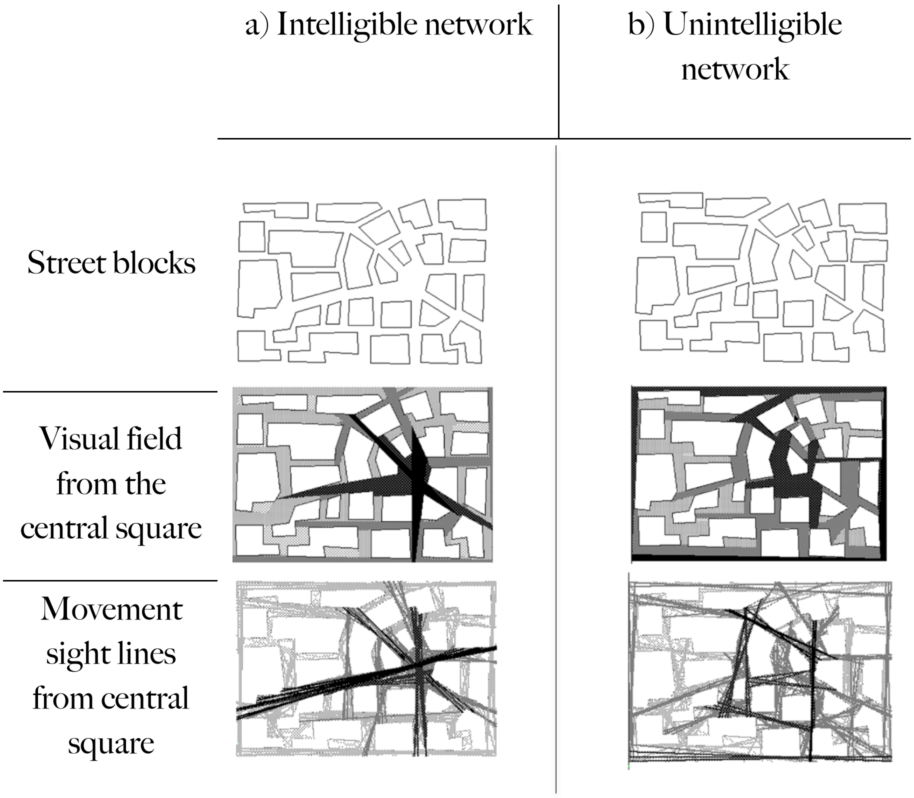
Some of the spatial factors that affect a *potential offender's* behaviour already have already been discussed. Crime Pattern Theory suggests (1984) that the way street network affects an offender's route choices, contributes to their overall awareness of space and criminal opportunities. Brantingham and Brantingham (1981 b; p.11) state:

> Criminals tend to commit their crimes near their major paths, but will explore around them. The exploration appears to be limited and tied to known or easily knowable spaces or places.

However, it is not only route choices that contribute to offender spatial awareness, but also how the arrangement of the network enables them to perceive aspects of the parts of the network that are nearby, but that they do not necessarily travel along. That is, how easily the unknown parts of the network can be inferred from the known locations that a person visits during trips between destinations. For example, in the simplest case, from a junction it would be easy to gain awareness of what is to be found on a connected street if that street has a straight layout. However, less would be known about that street if it had a more convoluted layout. At the neighbourhood level, depending on the arrangement of the layout, the street network makes it easy or difficult to infer about what is happening near by. It is argued (Hillier 2007) that successful navigation in an unfamiliar environment depends on how good a representation of the whole arrangement of the street network can be derived from its local parts (Recent research from environmental psychology supports this proposition, e.g. Barton et al. 2014). Scholars (Hillier 2007) suggest two types of street network layouts that can be observed in cities:

- *intelligible street networks*, where the urban form permits the ease of movement from the local neighbourhood to the regional city scale;
- *unintelligible street networks*, where the urban form permits the ease of movement locally, but the street network has poor or disordered connections for regional scale movement.

Figure 3: Two types of street network in terms of movement permeability from local to regional scale



Modified from source: Copyright © Bill Hillier 2007.

Figure 3 provides illustrations of two examples of the two different arrangements of the same urban blocks in a neighbourhood. In the first example (**Figure 3a**), the street network can be referred to as an intelligible street network since it facilitates the visual and movement access from the city centre to its periphery. Thus, a person standing in the middle of the layout has sufficient information about the local structure of street connections, but also through the visual fields he/she can differentiate between primary and secondary streets that lead to the periphery of the neighbourhood.

In the second example (**Figure 3b**), the visual field of the longest streets is blocked by the urban form. Thus, not only will it many more street segments have to be traversed to reach the edge of the neighbourhood, but the local street connections may mislead about the large scale street layout of the neighbourhood. So, this street network is unintelligible since it does not convey enough information to a person about how to navigate effectively through the network.

That is, an offender's awareness space might be constrained not just by the parts of the network they frequent, but also by the visual and topological properties of those elements of the street network that are nearby. This is not to suggest that from the crime prevention perspective unintelligible layouts are better for crime prevention, but to highlight that by studying street network layouts more formally using techniques from Urban Studies, more insight could be gathered as to why particular street segments are more prone to crime. It might also be useful to study the offender's route choices not by measuring approximate 'as the crow flies' distances, but using methods that also look at the topological properties of the street grid. In this sense, the use of techniques that analyse street segments with the inclusion of some cognitive route selection processes, such as, for example, visual fields and the linearity of route selections, or intelligibility of the street system, might provide new insight into offender spatial decision making.

Scholars (Beavon et al. 1994) have additionally emphasised that crime patterns will vary spatially depending on whether the offender walks, takes public transport or drives a car. Moreover, that offenders tend to select targets near to their home neighbourhoods (Feeney 1986; Rengert et al. 1999; Bernasco 2009; Rossmo 2000). Given the mentioned above facts, a minimum of two movement types can be observed in the area:

- residents moving in, out and around the neighbourhood,
- visitors and strangers moving in, out and around the neighbourhood.

A potential offender may be a resident of a given neighbourhood, a stranger to it who resides nearby, or they may be from a completely different location in the city. In the latter case, consideration should be given to how permeable a location is for public and vehicular transport (Hakim et al. 2001; White 1990) or how permeable are the neighbouring areas. The key factor is that the spatial arrangement of the street network and the level of permeability significantly vary in relation to the reference location (Hillier and Hanson 1984). That is, the offender's location and subsequent accessibility of the whole neighbourhood will dramatically differ depending on whether the offender is from the same area or just a passer by. For example, if an offender resides in an area they will most probably be around two to three streets away from almost all locations in the neighbourhood. However, if they are a visitor they may need to pass through many more streets in order to travel to the centre of the area or pass through it.

Furthermore, it can be proposed that an offender might be aware of opportunities present at certain locations, but the lack of social interaction between different groups of people, potentially increases the risk of crime as a consequence of *guardians being absent* from the given space or because they do not act to deter crime (Cohen and Felson 1979; Reynald 2010). For instance, scholars report (Bevis and Nutter 1977; Wright 1996; Bellair 2000 (for the review of the topic see Clarke 2004) that residential burglars avoid streets where passers-by might see them.

It is suggested (Jacobs 1961; Hillier 2007) that sufficient co-presence on streets can have an additional surveillance function when people are watching other people who use or move through the space. However, it should be noted that in order to detect unusual behaviour, people present on the street should be aware of the contextual situation as well, i.e. types of people passing by or activities taking place (Reynald 2010). Urban scholars (Hillier 2007) have suggested a 'safety formula', where the movement rate per length of street should allow the walking person to be in constant visual contact with at least one more person walking on the street. Scholars argue that for a moving individual, long uninterrupted lines of sight are considered an important factor of awareness of the situation and people passing by. This also influences the likelihood of different categories of people - such as old people, working adults, or children - being co-present on a street segment. It was proposed (Hillier et al. 1989; Hillier 2007; Zako 2009) that badly designed housing estates, with interrupted lines of sight; encourage only one type of visual interface to be present per space. For instance, there may be no interaction and visual control between children and adults. Thus, the absence of intimate handlers (Felson 1986) may provide opportunities for antisocial behaviour.

Conversely, it has been also suggested (Campos and Golka, 1999) that high co-presence and informal surveillance of passers-by occurs in those spaces that have many movement routes passing through a single space that has good visual coverage. Urban squares and plazas often possess this kind of spatial arrangement. Thus, as well as influencing movement patterns, the geometry of street segments influences visual fields, which may in turn affect offender location choice.

As well as facilitating through movement, street segments simultaneously act as destinations. For example, high streets facilitate movement flows but act as destinations at which various people interact in the space (Vaughan *et al.* 2013). Street segments that combine both kinds of movement might be particularly influential on crime patterns formation, since they attract much more movement volume to the area and hence will be explored in this research.

Crime targets also have a strong spatial component. Scholars (Hakim et al. 2001, Bowers and Johnson 2004, Hillier and Sahbaz 2009) showed that after accounting for opportunity, some places are more vulnerable to becoming a target than the others. It has been illustrated that among many targets the combination of certain spatial, social or economic factors make particular places more attractive for crime. In the case of burglary, scholars found that flats or houses located on the corners of the streets are more prone to burglary crime than those located in the middle of the street block (Rengert and Wasilchick 1985; Cromwell et al.1991); houses bordering on open green areas or a playground are also more vulnerable (Hakim 1995); detached houses are more crime prone than semi-detached or apartment blocks in the wealthy neighbourhood (Hakim et al. 2001). Also there is 'safety in numbers' (Hillier and Sahbaz 2009), where the risk of being a victim of crime is distributed among many potential targets or individuals. For instance, for an individual, becoming a victim of pickpocketing on a crowded street is less risky than on a neighbourhood where few people pass by (Hillier and Sahbaz 2009). Besides, there is a spatial interaction within neighbourhoods: a small number of affluent residential houses located near a high street are more prone to crime than the same number of houses located in a residential area. Cul-de-sacs may become safer with both large number of neighbours and with less wealthy residents (Hillier and Sahbaz 2009).

2.1.4 Street permeability as a variable in crime research

In general permeability can be defined as a property of the street network that permits movement through the urban layout. Depending on the crime type, offenders may be more or less prone to seek out permeable locations to commit a crime. For instance, pick pocketing (or other crimes of stealth) may be more likely occur on permeable streets and near bus stops (Loukaitou-Sideris 1999; Hillier 2004), where large number of potential victims congregate, while other crimes may be more likely on less permeable locations – car theft (Clarke and Mayhew 1994) where offenders avoid guardianship.

That is, depending on the types of crime, permeability may encourage or discourage offending. This section of Chapter 2 discusses the issue of *street network permeability* in relation to the crime of burglary in residential neighbourhoods. This crime type was selected for two main reasons: it has received the most scholarly attention from studies of both Environmental Criminology and New Urbanism disciplines and, despite many studies being conducted there are still controversies regarding the influence of permeability on crime risk. The following discussion is based on a review of thirty studies that looked at street networks and examined burglary in relation to the level of street permeability.

Inspired by Crime Pattern Theory, previous studies (Brantingham and Brantingham 1984, Beavon et al. 1994) have proposed that the way offenders travel across the street network determines their knowledge of potential victims or targets. Scholars (Rengert 1980; Hillier and Shu 2000; Johnson and Bowers 2010) have further suggested that the degree of street network permeability affects the relative risk of being targeted as a result of being located on those paths. The main findings that all researchers agree on are that both the neighbourhood spatial layout and residential movement mobility affect the level of crime. What is not clear from the empirical research, is what type of layout increases or decreases the risk of crime. This uncertainty leads to the main argument – *Is a high level of permeability good or bad for crime?*

Particularly in the case of burglary, the controversial issue is that through movement within residential areas can theoretically have diametrically opposing effects. To explain, consider that permeable locations are those that are well connected and encourage movement within the neighbourhood. According to crime patter theory, this can increase a criminal's spatial awareness of crime opportunities in the area, making such locations more risky than less permeable locations. On the other hand, scholars taking a new urbanism perspective (Jacobs 1961, Hillier, 2007) argue that the separation of places and the use of hierarchical street layouts (which are less permeable) creates a lack of interaction between different categories of people, which leads to limited pedestrian movement in the neighbourhood and as a consequence less surveillance on the street. From this perspective, all else equal, less permeable street segment would the ones anticipated to have the highest risk of crime.

Table 1 summarises a comparative analysis of a sample of the literature (eight studies) that used street permeability as an independent variable to try to explain patterns of burglary in residential neighbourhoods. In almost all cases, explicitly or not, the topological characteristics of street network were examined. In many instances, the connectedness of a given street segment alone is defined as a measure of relative permeability (Bevis and Nutter 1977; Beavon et al. 1994), where the number of turnings (i.e. connectivity) from a street block indicates how permeable the block is to its immediate surrounding neighbour streets. However, when comparing across studies, it becomes evident that different scholars define permeability in various ways. Specifically, across studies, permeability was defined:

- **in relation to main traffic flows**, for instance how far the given street block was from major traffic highways (Hakim et al. 2001) or how many access lanes to the traffic arteries a given neighbourhood has (White 1990);
- **according to the type of road or footpath** that leads to shops, other residential areas, other footpaths, streets with high pedestrian and vehicle movement (Armitage 2007);
- **as a topological property of the segment,** that is how permeable is the given segment in relation to all other segments in the study area (Hillier and Shu 2000);

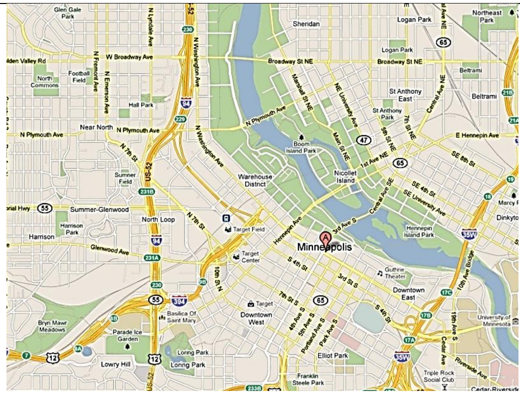
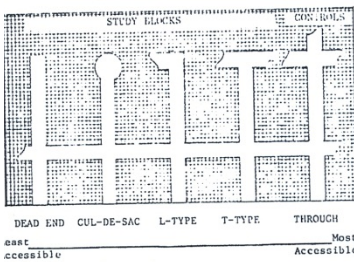
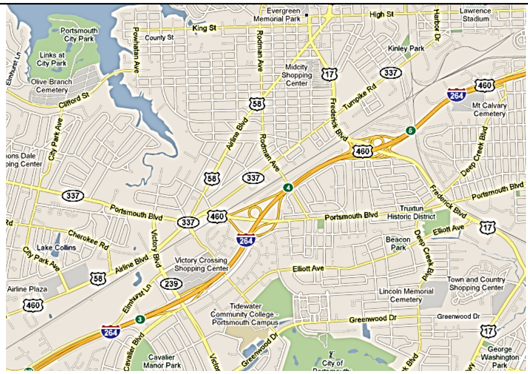
- **according to the type of road and number of connections**, for instance how many direct connections the given segment has, and to which type of road the latter one is connected (Johnson and Bowers 2010).

The difference between the studies can be clearly traced in the argument related to cul-de-sacs and whether or not they increase the risk of crime. From **Table 2** it can be seen that cul-de-sacs were defined according to topological permeability (Bevis and Nutter 1977; Beavon et al. 1994 ; Armitage 2007), geometrical layout and topological permeability (Johnson and Bowers 2010) and configurational permeability, i.e. the measure is derived from the way street network is arranged (more thorough definition is presented in Chapter 3) (Hillier and Shu 2000, Hillier and Sahbaz 2008). Also there was a distinction made between vehicular and pedestrian cul-de-sacs (Hillier and Shu 2000; Armitage 2007). Putting these issues aside, the dominating opinion regarding houses located in cul-de-sacs is that they have a lower level of crime compared to houses situated on through roads. However, opinions differ regarding which type of cul-de-sac (true or leaky) with which shape of geometry (sinusoid or linear) is the safest.

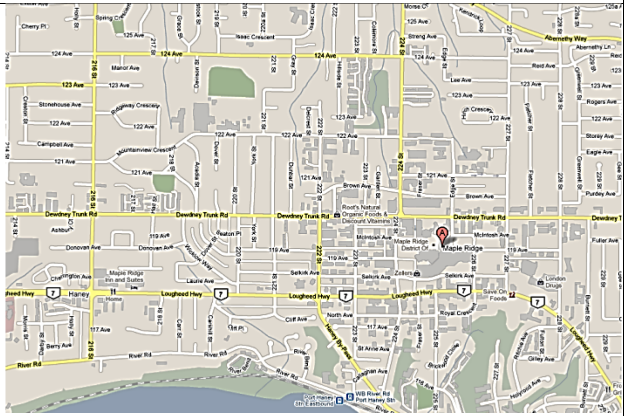
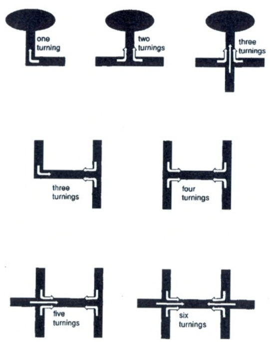
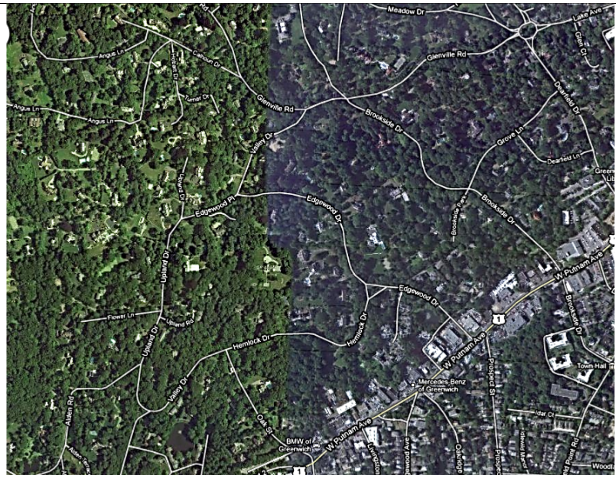
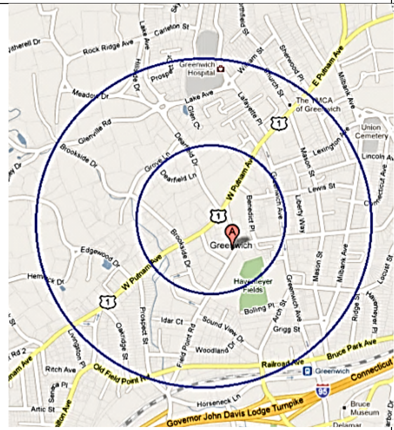
It can be proposed that this variety of findings is due to many reasons, including:

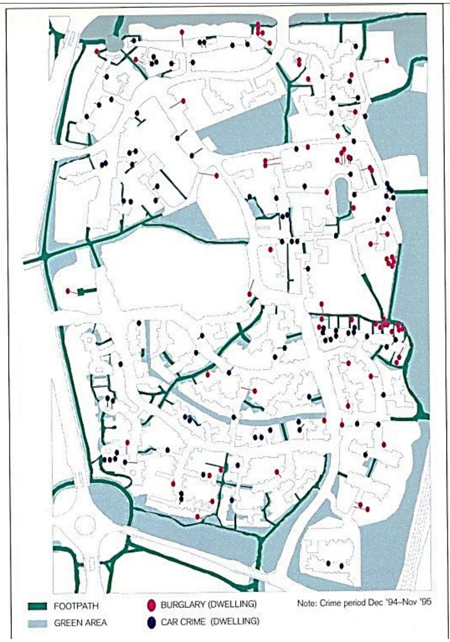
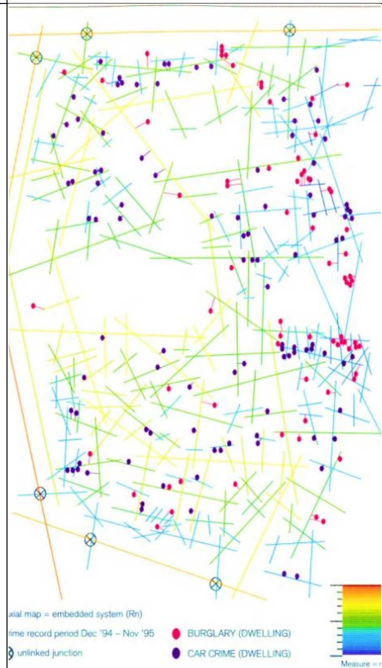
1. The difference between the type of street network that is examined: from regularly planned *grid like* neighbourhoods (Bevis and Nutter 1977; White 1990; Beavon et al. 1994) to unplanned (Armitage 2007; Hillier and Shahbaz 2008) or hierarchically planned *tree like* neighbourhoods (Hillier and Shu 2004; Johnson and Bowers 2010).
2. The difference in the type of movement that the study examined: that is how permeable the given *street segment* or an *area* is for car traffic (Bevis and Nutter 1977; White 1990; Beavon et al. 1994) or pedestrian movement (Hillier and Shu 2004; Hillier and Shahbaz 2008).
3. Different models of street network spatial conceptualisation: proximity as a metric distance (Hakim et al. 2001; Armitage 2007), topological connectivity (Bevis and Nutter 1977; Beavon et al.1994), topological connectivity with geometrical linearity (Johnson and Bowers 2010); and topological connectivity with geometrical change in angle of connection (Hillier and Shahbaz 2008).

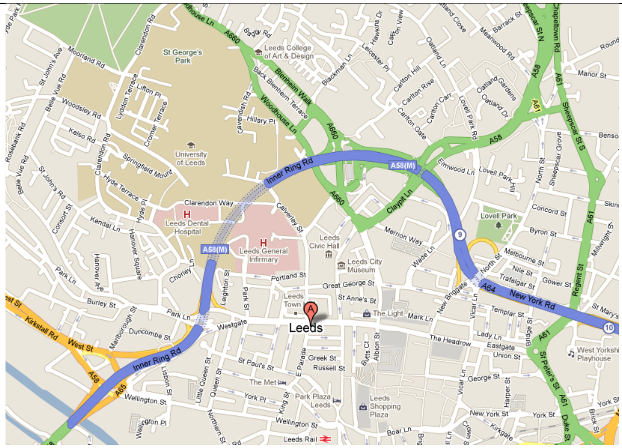
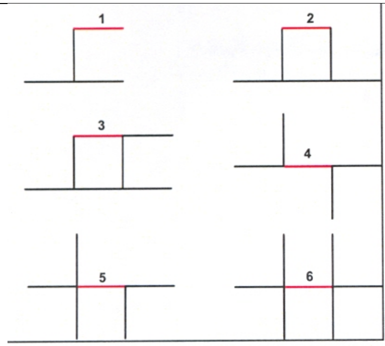
Table 1: A comparative analysis of studies that looked at burglary crime and street network permeability

NAME	LAYOUT OF THE STUDY AREA [1]	THE DEFINITION OF PERMEABILITY		MAIN FINDINGS
Bevis and Nutter (1977, North American study)			The permeability is measured by the number of directions from which a car could enter or leave a representative block.	The results show that dead end, cul-de-sac and L-type blocks have lower residential burglary rates than do more permeable control blocks. However, T-type blocks had higher rates of burglary than their accessible control blocks.
White (1990, North American study)[2]		$\text{Permeability} = \frac{N\ of\ access\ lanes}{1000\ households}$	Permeability as a rate of the numbers of access lanes (from the neighbourhood to automobile traffic arteries) per 1,000 households.	Permeability was a significant influence on neighbourhood burglary rates when neighbourhood economic factors, instability, and structural density were controlled for.

[1] Whenever no representation is specified by the author the Google map of the given study area is used as an example of type of grid that was examined.
[2] For this study, the unit of analysis was the area.

NAME	LAYOUT OF THE STUDY AREA	THE DEFINITION OF PERMEABILITY		MAIN FINDINGS
Beavon et al. (1994, Canadian study)			Permeability was defined according to number of 'turnings' into each street segment and combined with a traffic flow variable according to 'feeder', 'minor artery' and 'highway'.	Those blocks with both high accessibility and high street flow had a disproportionately greater amount of crime.
Hakim et al. (2001, North American study)			Accessibility to major arterial roads as an ordinal variable (homes from 0-0.25 miles, 0.25 - 0.5 miles, 0.5-1miles, 1 and more miles away from arterial roads).	The highest probability of burglary was observed for homes that were expensive, located on a dead-end street, were detached single-family corner homes located within a quarter of a mile of an exit from a major thoroughfare, and those that were adjacent to woods.

NAME	LAYOUT OF THE STUDY AREA	THE DEFINITION OF PERMEABILITY		MAIN FINDINGS
Hillier, Shu (2000)			To-movement is about the closeness or accessibility of spaces from all others. This is referred to as integration in the space syntax literature. Higher integration values indicate more potential movement and better visual connection. Integ = NC / MD Where NC is node count (i.e., the number of nodes within a "cookie cut" radius), and MD is mean depth of the nodes with respect to the root node.	The public spaces from which burglary is least likely to occur are those on through carriageways, with good movement potential and visual links, and with a good number of line neighbours opening on to both sides of the carriageway. Those for which the risk of burglary is highest are those that are rear dead-end footpaths with little movement and visibility and few line neighbours. Negative features are visually and permeably broken-up spaces, with poor movement, few line neighbours, poor indivisibility and spaces without front entrances.

NAME	LAYOUT OF THE STUDY AREA	THE DEFINITION OF PERMEABILITY		MAIN FINDINGS
Armitage (2010, UK study)		Higher permeability is defined as proxied by the property's proximity to a footpath, whether that footpath leads to shops, other residential areas, a maze of other footpaths, and the level of pedestrian and vehicular movement through the estate.	Permeability was ranked according to a checklist which identified seven categories of road network, access, if a property was within the awareness space of others, surveillance or parking. Police records were compared to houses ranked on the basis of these environmental features.	The environmental factors which emerged as associated with elevated crime levels suggest that higher levels of movement past the house are generally associated with higher levels of risk.
Hillier and Sahbaz (2008, UK study)			Segment connectivity was compared with residential burglary risk. Segment connectedness was assessed in relation to tax bands (an index of deprivation) and the number of dwellings on the segment.	Higher connectivity was associated with lower burglary rates. Both for high and low connected segments the greater the number of dwellings on the segment, the lower the burglary rate. Most at risk were small groups of affluent houses in poorly connected locations.

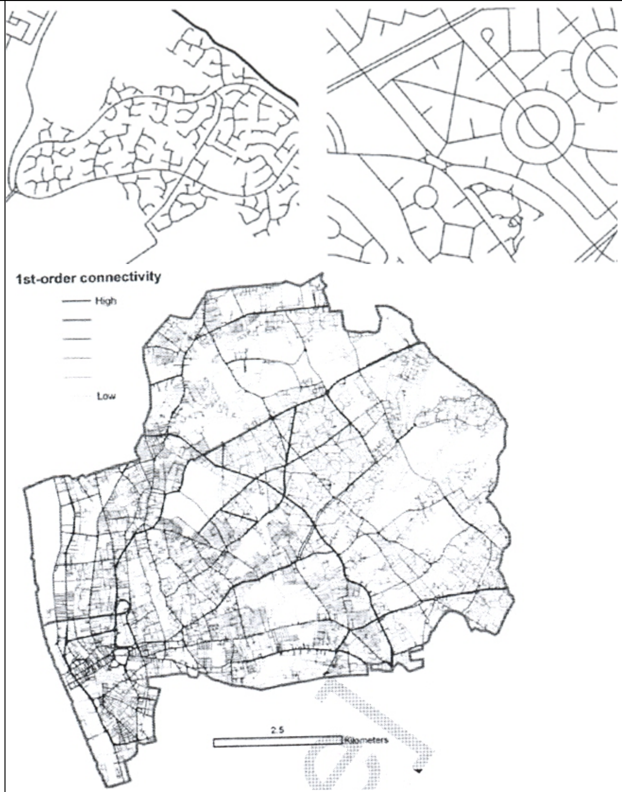
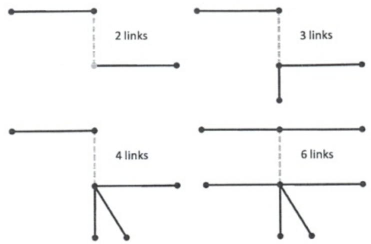
NAME	LAYOUT OF THE STUDY AREA	THE DEFINITION OF PERMEABILITY		MAIN FINDINGS
Johnson and Bowers (**2010, UK study**)			For every street segment the number and type of other segments directly connected was calculated. To show how connectivity varies across the network the authors multiplied the number of roads of each type by the rank order of accessibility for that type of road (roads were classified as 4 for major, 3 for minor, 2 for local, 1 for private, also linear and sinuous cul-de-sacs). Computed higher values will indicate greater connectivity to more major road segments. Aggregated results expressed as the rate of burglaries per 1,000 homes for each type of street segment. Authors also accounted for area level factors, including socio-demographics.	Findings show that connectedness to carry an elevated burglary risk, particularly where connections are to more major roads.

Table 2: A comparative analysis of studies that looked at burglary in relation to street network cul-de-sacs

Bevis,Nutter (1977)	Beavon et al. (1994)	Hillier and Shu (2000)	Hillier and Sahbaz (2008)	Armitage (2010)	Johnson and Bowers (2010)
			THE SPATIAL DEFINITION OF THE CUL-DE-SAC		
Linear with one connection cul-de-sac	One or two turnings to cul-de-sac	Cul-de-sac carriageways Cul-de-sac driveways Cul-de-sac front footpath Rear dead-end footpath	A segment with one and up to three connections (hierarchical cul-de-sac) was identified as cul-de-sac.	Cul-de-sac without linked pathway Cul-de-sac with linked pathway Footpath runs at rear of house	*Linear cul-de-sac* (off through roads)- cul-de-sacs that were linear in geometry and were one turn off a through road (major, minor or local roads). *Sinuous cul-de-sacs*-roads that were non-linear in geometry so that there would be little visibility down the road from the road to which they were connected.
			MAIN FINDINGS		
Dead end and cul-de-sac blocks have lower crime rate than do their more accessible control blocks.	The street accessibility increases, the number of reported property crimes also increases.	Where cul-de-sacs are linear carriageways, attached to and visible from linear streets with continuous front entrances, and have enough line neighbours, they can do quite well. Those from which you are most likely to be burgled are rear dead-end footpaths with little movement and visibility and few line neigbours.	Cul-de-sac or near cul-de-sac, is not safe itself, but it becomes safe with larger, not smaller, numbers of neighbours, and with less affluent occupants. Property located on leaky cul-de-sac is estimated to have 110% more crime than property located on the true cul-de-sac.	Property located on through road experienced 93% more crime than property located on the true cul-de-sac. Properties overlooked from the rear by three to four properties have 38% fewer crimes compared to those that were not overlooked.	Cul-de-sacs have lower rates of burglary, and this is particularly the case for those that are linear in geometry.

2.1.5 Different movement cultures and crime

In addition to methodological differences, the variation in findings discussed above may be due to cultural difference in movement mobility and street layout arrangement. For example, patterns may vary for vehicular dominant and orthogonal grid-like North American cities, and pedestrian dominant and unplanned European cities. These differences will reflect both the particular street types used for movement between locations and the scale of the journey. For instance, pedestrian movement operates across greater types and layouts of street segments than vehicular movement does. As a rule, pedestrian movement has greater permeable access across the street network than vehicular movement. However, in some countries, where vehicular movement dominates, this relationship might be equal or even prevailed by the latter one, due to both greater distances between origins and destinations, and the common regularity in street network layout. **Table 1** shows that similar to European studies (Johnson & Bowers (2010) and Armitage 2010) the studies that examined street networks with orthogonal grids found that greater permeability was associated with a high level of crime (Bevis and Nutter 1977; White 1990; Beavon et al. 1994). It can be proposed that since all streets in this type of street network are similar in length and there is little variation in street connectivity and angularity of segments, where high mutual indivisibility dominates across the street network, combined with a small number of pedestrians on the street, this provides greater criminal mobility and more opportunities for crime.

Several scholars from Space Syntax (Hillier and Shu 2000) have reported that more occurrences of crime are observed on less permeable street segments where there is insufficient interaction between different types of people, which results in less surveillance on the street. Interestingly, several non-UK studies, mainly from North and South America (Reis et al. 2003, Nubani and Wineman 2005, Farooq 2007) reported findings that are not consistent with this hypothesis. That is, a high level of crime incidents are observed on residential roads with high integration values. This does not suggest that the theory of natural movement is insufficient to explain the phenomenon; on the contrary, the authors of these studies concluded that the main reason for the contrasting results may be due to cultural differences in the organisation and routine for pedestrian and vehicular movement. For instance, in the North American cases scholars reported a very low number of pedestrians moving on the integrated streets, whereas in the South American cases, a large number of pedestrians were observed to move through the streets, especially in residential areas called favelas. It seems that in the case of North America, although the street network provides permeable spaces for potential movement, the fact that the society is automobile dependent dominates over the layout, which leads to less co-presence and consequently less surveillance in the space. In contrast, in South America, it might be the case that a large number of people walking near residential units do not allow cohesion between the neighbours, since the street layout generates too many encounters of different people. That is, where too many strangers are found in an area, this might affect both the perception of security and crime patterns negatively. It can be proposed that given that the distribution of movement and the co-presence of people is not constant across the street network; both an extremely low and high number of movements on the street might influence the probability of crime occurrence.

In addition to the issues discussed, there might be other methodological reasons for expecting the differences in empirical findings:

- Inaccuracy of the source data or incorrectly defining the layout of the footpath or cul-de-sac;
- With spatial environment where everything is interconnected, the sampling does not account for significant variation in the different layout of the street networks, such as grid, tree or hierarchical like layouts. Thus, by analysing individual neighbourhoods the relations observed at one location might not be the same across the spatial network.
- Not accounting for the spatial dependency in the data. That is, the first law of geography states that the closer the observations are in space, the more they will influence each other (Tobler1970). Where dependency in the data exists, failing to account for this violates the requirements of conventional statistical tests. Few studies (exceptions include the studies by White 1990; Johnson and

Bowers 2010; and Armitage et al. 2011) have employed robust inferential statistical methods that account for such dependency in the data.

2.2 Drug crime locational choices

2.2.1 Theoretical rationale

As discussed, crime opportunities are not randomly distributed across the urban environment, but have some spatial ordering. This ordering somewhat depends on the daily routine of both the offender and the victim, and on how they both navigate during their daily routine across the street grid (Cohen and Felson 1979; Brantingham and Brantingham 1984). This rationale was used by scholars (Eck 1995, Rengert et al. 2005) in order to explain how both drug buyers and dealers identify places that are potentially suitable for transactions of the kind in which they involve themselves.

It is proposed that rational decision making on the part of both participants – buyer and dealer - in the transaction influences the geographical distribution of drug dealing locations (Eck 1995). Depending on the method of transaction, drug markets can be very large and dispersed, or small and more concentrated (Eck 1995). Scholars (Rengert et. al 2005; McCord and Ratcliffe 2007) have identified that profitable drug markets are often situated in or near socially disorganised neighbourhoods, where there is a lack of social resistance to the market's existence and from which there may be a ready supply of people willing to purchase drugs. However, the rationale for choosing these neighbourhoods remains disputed: it is still unknown whether the locations are chosen initially due to their accessibility to a large number of drug users and their presence undermines the neighbourhoods' social organisation (Eck 1994) or whether the initial lack of social resistance provides optimal grounds for establishing drug markets (McCord and Ratcliffe 2007).

Additionally, it has been noticed that the success of trading locations is associated with types of land-uses that are conducive to, or generate, other types of crime. For example, drug dealing is likely to happen close to facilities, which inherently and routinely generate a large flow of people. These are mainly open public spaces, retail, entertainment facilities and transport interchanges that are associated with low levels of adequate guardianship or place management (Eck and Wartell 1996). In their analysis, Rengert and colleagues (2000) defined two types of built environment facilities that may be associated with the locations of drug markets. First, there are those, which indirectly increase the profits from drug sales, because they facilitate non-residents' access to an area. An example of this would be transport interchanges, which provide easy access to the drug markets (Brantingham and Brantingham1995). Second are those, which generate opportunities for drug transactions because potential drug buyers use them routinely. For example, areas near to homeless shelters or money lending shops, where potential buyers can readily convert stolen goods to cash (Anderson 1999).

2.2.2 The main dilemma

In the same way that legitimate businesses do not select their location at random, drug market placement may reflect rational decision making (Eck 1995, Rengert et al. 2005): the main aim of both activities is to attract customers and supply products to them in order to make a profit. From a strategic perspective, when deciding where to locate their stores, retailers focus on finding an accessible spatial location, which will attract many potential customers. However, their locational choices are also constrained by different planning regulations and environmental impact assessments, which are required by authorities to allow the placement of the shop.
Rengert et al. (2000) suggest that drug dealers may follow a similar logic and try to identify potential profitable sites. As Rengert states, 'the quality of the sale's location is directly related to the quantity of profit for the illegal drug sales' (Rengert 1996:220). However, in contrast to legitimate trading, in the case of illegal markets offenders have an additional goal: staying safe and unnoticed so as to avoid arrest (Reuter and MacCoun 1993). Thus, drug dealing locational choices are also constrained by the presence of legitimate and capable guardians who discourage criminal opportunities (Eck 1994). These include security guards, home and shop owners and generally people who manage such places. In their study of drug and disorder problems, Mazerolle et al. (1998) found at the level of street blocks, that the place managers, who engaged in crime prevention activities, played an important role in guarding places from drug problems. Moreover, they found that place managers who engage

their neighbours from the same street block in crime prevention efforts, are more effective than individual efforts.

Eck (1995) has termed this specific aspect of drug markets the accessibility vs. security dilemma: 'how to exchange illicit goods or service when the exchange process is very risky' (1995:71). Illicit drug markets typically face the conflict between needing to be accessible to many customers, including complete strangers, and avoiding the vulnerabilities associated with drug sales. Due to the illicit nature of the market, both customers and dealers are usually in a vulnerable position, since they run the risk of both legal intervention and being cheated or robbed by their counterpart during the course of a transaction. Of course, there is no means of securing the transaction through law enforcement, or of resolving such conflict of interests through legal channels (Reuter and MacCoun 1993). Thus, violence is a very common means of regulating and resolving disagreements (Goldstein 1985), especially in street-based sales, where exchanges take place outdoors, often between anonymous participants. Both buyers and dealers will thus be motivated to limit their accessibility so as to reduce risk, seeking locations that they personally consider to be safest. Such places may be enclosed and familiar locations. For example, indoor sales may be made from fixed locations such as drug houses, or deliveries made to indoor locations specified by the customers (Curtis and Wendel 2000). However, in both of these scenarios, one of the participants will always be at a greater risk than the other, since they will not be familiar with the location. In some cases, unfamiliarity may lead to them avoiding a location altogether.

Eck (1995) proposes two models of drug markets, which can overcome the access-security dilemma, given the constant risk of police presence. The first is the *social network based transactions model*, in which security is provided through a network of trusted people. The second is the *routine activity model*, in which both participants use their legitimate daily activities to search for places, which are potentially appropriate for engaging in drug deals. In the first model, there is no attachment to a specific location; through a social network both parties can arrange a mutually accessible location, potentially based on their routine. This type of market tends to be closed in nature and the market itself may be dispersed over a large geographical area, leading to a low spatial concentration of drug dealing incidents (Eck 1995). Although a network-based exchange offers security, it also limits the number of participants in the transaction, which in turn reduces the potential for profit.

The second model proposed (Eck 1995) assumes that the spatial-temporal patterns of both participants' legitimate daily activities determine where their drug transactions occur. These markets tend to be spatially clustered and to focus on locations which are familiar to both participants, thereby reducing their perception of potential risks. These markets also need specific operating conditions; when surrounded, for instance, by a large number of legitimate activities and a constant flow of foot traffic, it is easier to blend into the crowd and search for potential customers. This type of market is often an open street market with a high frequency of transactions between anonymous participants. The market permits equal access to all participants and is located near places with mixed land uses and a high concentration of activities, such as shopping centres, high streets, transport interchanges and others. Eck (1995) proposes that place managers from the legitimate sphere who control and manage these locations have a particularly important role in impeding this type of market.

It should be noted that not all locations, which are next to shopping malls or transport facilities, for example, would form drug markets. According to this model, places which are more likely to have drug markets, will be attractive from a retail perspective, offering a balance between the spatial distribution of those who demand the product, and the distance they would be required to travel to the market. This concept will be discussed further in the following section.

2.2.3 Drug crime locational choices and spatial economics

As with many crime types, open drug markets tend to concentrate geospatially; from all the available urban locations there are very few which are well-suited to illegal drug trading. Weisburd et al. (2004) found that a small number of street junctions in Jersey City (4,4%) accounted for almost half of the drug sales arrests in the city. This demonstrates considerable spatial concentration of markets. According to Kleiman (Kleiman 1991 cited in Taniguchi et al. 2009) the reason for spatial clustering is that a large number of dealers operate in a single location, gaining security from arrest by spreading the risk of apprehension across all dealers. The same logic applies to customers who would prefer to be in a crowd than alone.

Rengert et al. (2005) propose that the exact location of open drug markets is likely to depend on the convergence of conditions that are most suitable for both participants involved in transactions and spatial patterns in demand. They suggest the model of 'agglomeration economics' operates, as is the case with legal trade. That is, after a location becomes known as a site for specific goods, more customers will visit the area in the search of that good. At a certain point, the number of buyers that visit the area will be sufficient to support further suppliers of the product(s) and so more retailers locate there. In Wilmington, USA researchers discovered that the likelihood of large drug markets being located near to each other is quite high. They say 'there are best places to sell illegal drugs because these are places where demand is focused spatially' (Rengert 1996). That is, in order to stay profitable, a drug market's location should be attractive enough to a sufficient number of drug users. The attractiveness of the place is partially determined by the surrounding facilities, but above all by how far a buyer is prepared to travel to make a purchase (Pettiway 1995).

In legal trading, markets for goods, which are highly valuable but purchased infrequently are usually found in very accessible urban locations, which may attract many potential customers from remote locations. In contrast, local markets tend to supply items, which consumers will wish to purchase frequently but will be prepared to travel only short distances to purchase. In their study, Rengert and colleagues (Rengert et al. 2005) discuss concepts from the Economics literature - *threshold population* and *range* - to frame a discussion of how the demand for drugs and the distance required to reach a market is likely to affect the location and stability of drug markets. Threshold is defined as a minimum number of customers required for a market to stay profitable. The concept of range concerns the distance that a buyer is prepared to travel to purchase a good. Pettiway (1995) suggests that the spatial range of a market that caters for vehicular movement will be larger than one that caters for pedestrian movement. Simply put, if the demand for a drug market is situated within the physical catchment area (an area to which they do or will travel) of many potential drug buyers that market will remain stable or may even grow.

It is proposed that given that accessible drug dealing locations should offer good retail potential, drug marketplaces can be classified according to the level of pedestrian and traffic accessibility, which may bring potential customers to the area. It can be suggested that, depending on a market's geographical positioning in the city the level of accessibility will vary - from locally to regionally accessible markets. For example, Eck (1995) found that in San Diego, outdoor drug markets formed at locations about two blocks away from major transportation arteries, suggesting that they were regionally accessible markets. Importantly, this suggests that although offenders aim to sell drugs from accessible locations, they do not tend to do so on the major roads (presumably as a way of reducing risk). That is, for regionally accessible markets, operating in close proximity to major roads may offer an acceptable balance of custom and safety. In comparison, in Philadelphia, Rengert and colleagues (2005) found a high concentration of drug markets located in the suburbs, located away from major roads, suggesting that these marketplaces are oriented to local rather than regional demand.

Furthermore, since drug markets are established along routes, which are used on a daily basis by many potential drug buyers, the location and retail characteristics of these markets can vary considerably. Therefore, examining the movement dynamics and the distribution of land uses across the network will allow not only identification of the spatial regularities of drug crime patterns, but also classification and development of prevention strategies for the drug crime clusters that potentially form drug markets. As mentioned in the introduction, the rationale for this multidisciplinary study involves studying drug markets by combining empirical approaches from the disciplines of environmental criminology and architecture. The novel joint approach will examine the drug crime across the street segments in relation to the street network layout and its spatial characteristics. Although considerable research has been carried into drug crime geography, no single study exists that examined different measures of permeability in relation to crime patterns and combined those measures with different land use types within a single model. This research seeks to examine and account for spatial variation of drug crime patterns, by studying the street network properties and land use mosaic in the city. The next section details the main objectives and the design of the proposed research.

2.3 The present research

2.3.1 Three main objectives

The proposed research is concerned with the location of drug markets at the street segment level and whether their placement can be understood by studying the design of the urban environment in a novel way. Particularly, the research investigates the extent to which illicit drug dealing depends on the specific geography of places and on their amenities, what makes them attractive from an economic perspective and how the different characteristics of urban fabric influence the drug crime occurrences. Following this rationale, the research pursues three main objectives:

1. To uncover the spatial dimension of the drug market, mainly ***where*** illegal drug markets are located or drug dealing occurs across the street network. The aim is to understand whether or not there are common locational tendencies that explain the geographical setup of a drug marketplace in relation to the topological arrangement of street network.
2. To investigate ***why*** certain places on the street network are attractive for illegal trading, that is, given that drug dealers are seeking the goal of maximising profit, the research investigates the geographical properties of locations that facilitate illicit activities. Furthermore, it analyses the placement of drug incidents in relation to legal land uses. The research tests if there is a *criminogenic affect* from certain type of land uses and how strong it is.
3. To rationalise ***why*** drug-dealing incidents are arranged as they are, that is, to test whether or not the retail nature of different drug types sold across the neighbourhood has a similar logic to the way legal goods are distributed in the city.

These three objectives comprise the main three analysis chapters of this research, to be found in Chapters 5, 6 and 7 correspondingly. The three objectives will be tested systematically by looking at the spatial arrangement of urban fabric from local neighbourhood to the citywide scales.

2.3.2 The research design

The overall methodological approach of this research can be described as a quantitative top-down approach – where through case study examination the real world data are collected and a range of analytic techniques to include traditional exploratory data analysis, crime mapping, space syntax urban analysis and non-parametric spatial statistics are used to test associations between variables and to make inferences about the underlying processes. In order to quantify and examine systematically the potential differences in locations where drug dealing does and does not occur, event count regression models are employed. The crime count per unit of analysis is modelled against explanatory variable(s) of various spatial and categorical data for testing the hypotheses. Both crime data and explanatory variables are derived from geographically referenced data. The variables employed can be categorised into three distinctive types of spatial data: point data which relates to crime or land use locations on the street network, syntactical data, which refers to indexed topological properties of street segments, and travel data, which includes the notion of distance and travel time between discrete locations. Almost all hypotheses are tested using various combinations of these three categories of spatial data.

The main analytical strategy employed constitutes two stages:

1. The crime data are examined using exploratory data analysis and visualised through mapping. This allows an initial exploration of the association between patterns of different types of drug-dealing incidents across the street network and the explanatory variables.
2. A series of regression analyses are conducted to model the likelihood of drug dealing on street segments as a function of independent variable(s) at these and other locations.

In order to analyse the data this way, a *crime incident based street segment model* is constructed, which involved grouping crime events, land uses and other spatial datasets at the street segment level of analyses. A detailed description of all the components involved and procedures employed during the data construction, modelling and testing processes are provided in subsequent chapters (Chapter 4, Chapter 5, Chapter 6 and Chapter 7). The next Chapter 3 describes the case study area and provides an initial exploratory data analysis.

CHAPTER 3

General spatial trends of drug crime in the case study area

Introduction

In order to examine the geographical characteristics of urban places and their effect on drug crime placement data are analysed for a case study area. In this chapter, the case study area is identified and general trends of drug crime in this area are examined. The chapter consists of three parts. The first describes the two principal data sources: the case study area and its corresponding description of urban fabric, and the police crime records. The ethical procedures for obtaining and using police records are also discussed, as are the data cleaning and editing procedures employed. Finally there is a discussion of the assumptions regarding the validity of the data and its limitations.

The aim of the second part of this chapter is to highlight general spatial trends in the crime data. This is done with two objectives in mind: to introduce the geographical arrangement of crime incidents across the case study area, and to choose an appropriate spatial unit of analysis for subsequent hypothesis testing. First, the reasoning behind selecting an appropriate unit of analysis is discussed, followed by the introduction of data diagnostic methods. The third part of the chapter explores and highlights the spatial crime trends in the case study area at areal and street level of crime aggregation. The chapter concludes with the discussion of the results.

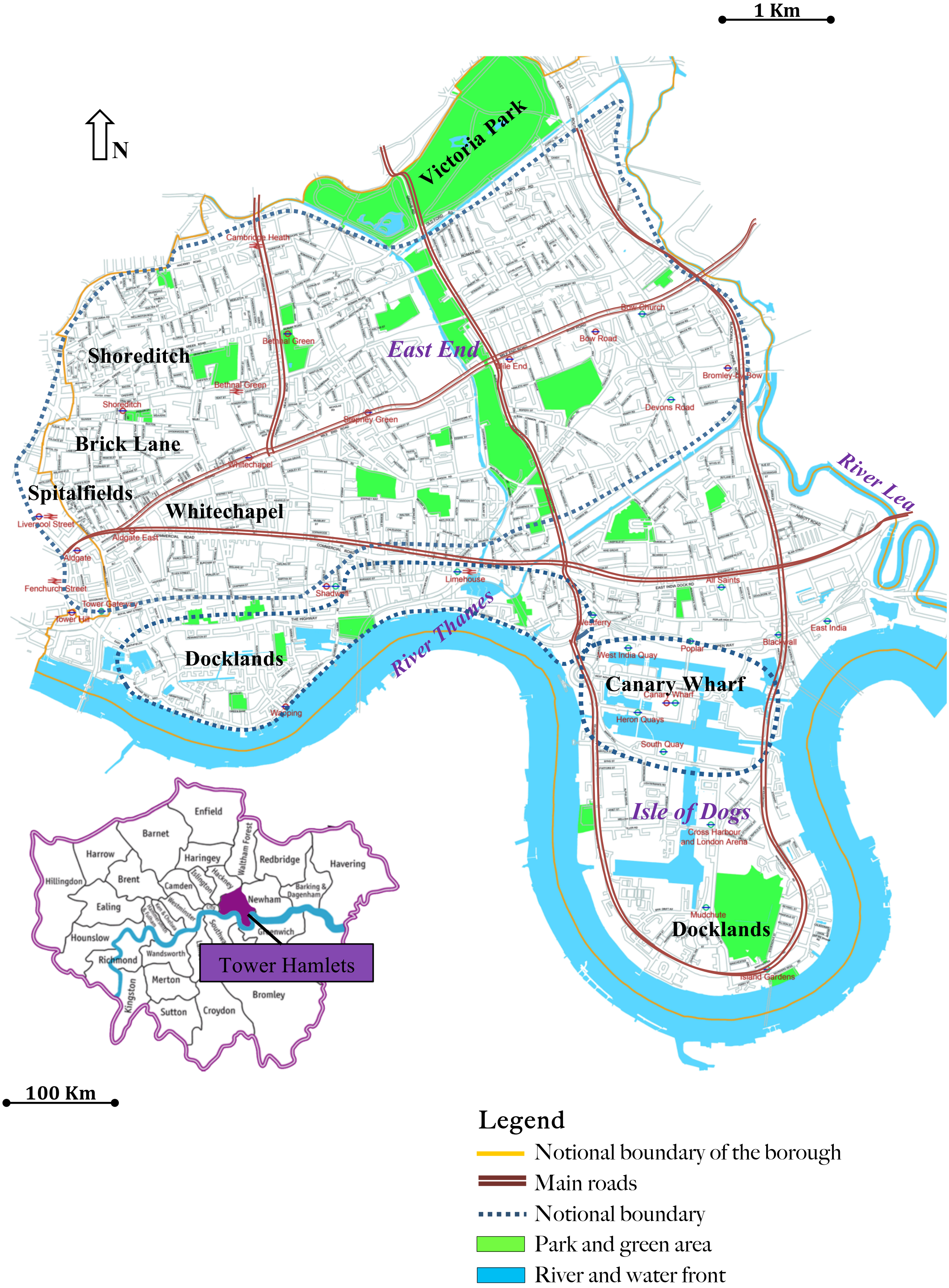
3.1 The case study area and crime dataset

In order to examine the patterning of drug crime at the small scale of geographical resolution, this analysis is conducted for a case study area. This allowed a detailed examination of drug crime patterns in relation to the different spatial characteristics of the urban fabric. In selecting the area to study, it was decided that the case study area should be an urbanised area with a large number of people visiting and residing in the area and that it should have a sufficient frequency of crime incidents. Based on these criteria, and availability of data in London the Tower Hamlets borough (see **Figure 1**) in the north east part of London in the United Kingdom was selected. Part of the rationale for selecting this borough was that it is known to have a high level of illegal drug activity. For example, according to recent statistics (see **Figure 2c**) on average the borough has a drug crime rate that is almost four times higher than the London average (score of 8.6) for the year 2009/10. This high frequency of drug crime offences offers a large sample of data to enable patterns to be studied at a small scale of resolution.

3.1.1. A brief geographical description of the case study

Tower Hamlets is located to the East of the city centre and borders with the City – the historical core of London. The borough is irregular in its geography with the south side facing the river Thames and the East side bordering the river Lea, see **Figure 1**. Out of the four boundaries in the case study area, three borders have natural barriers. Apart from the river Thames, a highway of regional significance passes along the east side of the borough from north to south. Additionally, a considerable part of the north border has a natural divider in the form of a park. For crime analysis, these features of the geography are important, since they eliminate the likelihood of the artificial partitioning of the area and the artificial creation of an 'edge' which can have a confounding effect in statistical analysis (Rengert and Lockwood 2009).

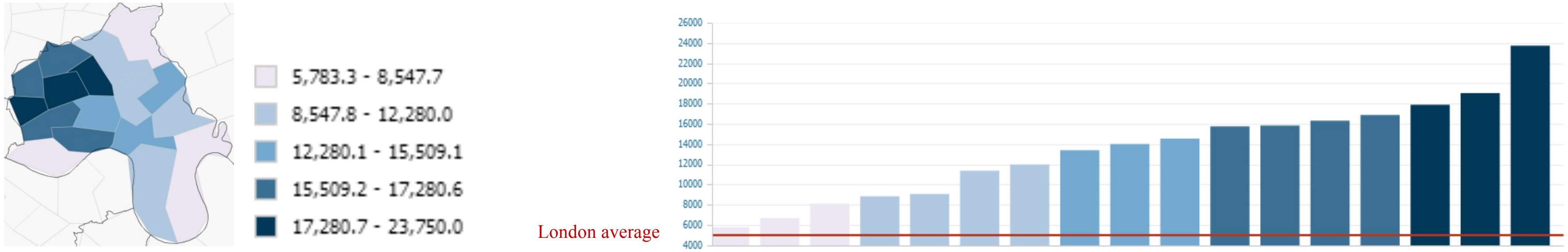
Figure 1: The schematic map of Tower of Hamlets Borough[3]



[3] Source adapted from http://www.faithintowerhamlets.com/default/1170.map/

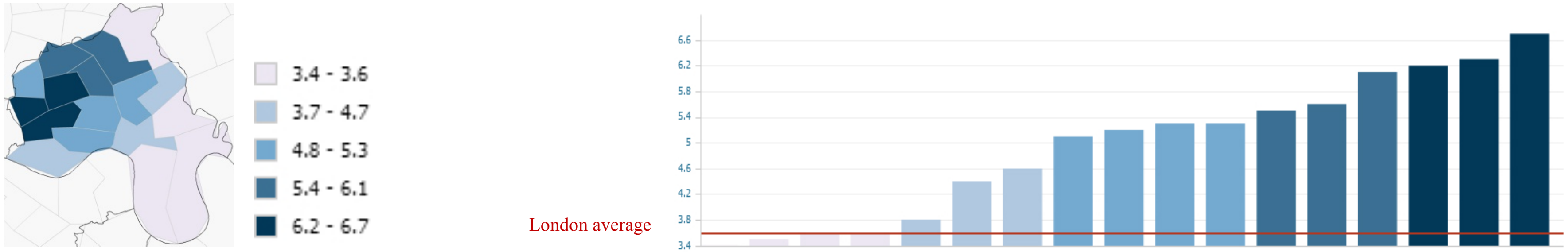
Figure 2: A summary of selected demographic data in comparison to the London average (rates are shown using a *quantile* distribution)

Population density (person per sq. km). London average score is 5, 069.



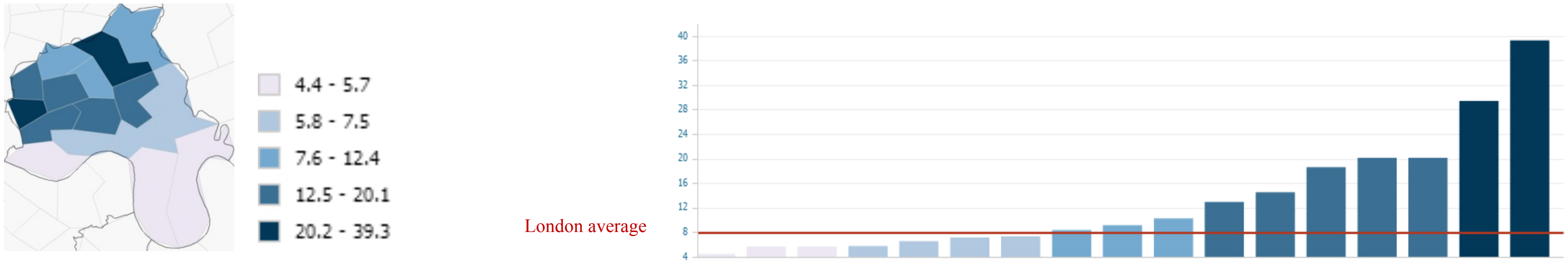
Population density

Public Transport Accessibility average score for the year 2010. London average score is 3.6.



Public Transport Accessibility

Crime: drugs rate 2009/10. London average score is 8.6.



Source: www. London.gov. Ward profiles [accurate as at 29th January 2013

Drug crime

The geographic area of the borough is 7.6 square miles and it has a population of 226,500 (the total London population is 8 million; 2012 census figure), see **Figure 1** and **Figure 2a**. This former dockland area has a very diverse urban context with a large variety of activities taking place across the urban fabric. According to Tower Hamlets Council[4], it has twenty-seven neighbourhoods, including one of the financial districts of the capital – Canary Wharf located on the Isle of Dogs, on the former area of West India Docks. Nowadays, it is redeveloped into high-rise buildings with office and retail uses. The nearby Dockland area along the riverside has also been redeveloped into residential housing and commercial land uses. Additionally, a considerable part of the East End of the capital is located in the borough and includes several diverse recreational districts with a large area associated with the night-time economy. The Shoreditch neighbourhood is one of the famous places in East End and it is associated with modern art galleries, media studios and a large variety of drinking establishments open until late at night.

The Brick Lane area is a small neighbourhood known for its Bangladeshi population and is popular for its annual festival, numerous curry restaurants, specialist shops and nightlife. The nearby Spitalfields area is famous for its Sunday markets. Apart from recreational land uses, the East End has numerous council housing estates scattered across the borough.

According to Ordnance Survey statistics, there are 59 health establishments in the borough including 21 hospitals of medium and large size. Tower Hamlets has 11 universities, 26 colleges and 92 schools. Moreover, a large variety of small to large green areas forming a total of 46 squares and parks, including one of London's largest parks - Victoria Park is located in the borough. The park is a popular venue for many annual festivals and concerts.

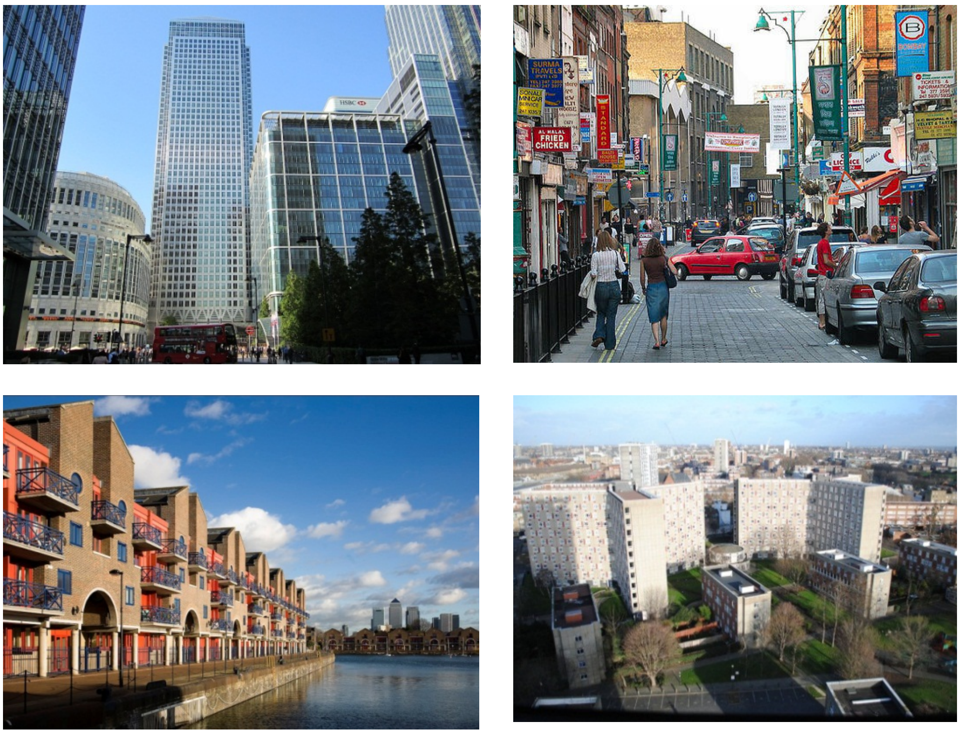
Both the road network and transport infrastructure are well developed in Tower Hamlets. The borough neighbours the City of London from which several roads of regional importance radiate towards east and south-east London. There are three underground line services connecting the area to the rest of London with 26 stations

[4] http://www.towerhamlets.gov.uk/lgsl/901-950/916_borough_statistics.aspx

located in the borough. Additionally, there are 31 day time and 7 night time bus routes crossing the borough. The average Public Transport Accessibility Level (PTAL) score is higher than the average score for the London area (**Figure 2b**).

Overall, the Tower Hamlets borough is a suitable case study area, since it has a sufficient variation of urban fabric distributed across an irregularly planned street network (**Figure 3**), it has well developed transport infrastructure and high rates of drug crime in comparison to other areas of London. A more detailed description of the urban fabric of the borough is presented in Chapters 5 and 6 along with the main analysis.

Figure 3: Examples of diverse urban environments in Tower Hamlets borough



Online resources: http://bit.ly/1wfLfrO; http://bit.ly/1wed2f3; http://bit.ly/YwoJNq; http://bit.ly/1pOiE77

3.1.2 Ethics of data protection and visualisation

To facilitate access to the crime data analysed, the researcher was cleared to Counter Terrorism Check (CTC) level and signed a data sharing agreement with the Metropolitan Police. Prior to data sharing, MPS officers removed any personal data related to the drug offenders from the data. Thus, only anonymised information regarding drug crime locations was provided. This was encrypted and securely transferred to the researcher. The data are stored in compliance with the 'seventh data principle' of UK Data Protection Act 1998[5]- *"Appropriate technical and organisational measures shall be taken against unauthorised or unlawful processing of personal data and against accidental loss or destruction of, or damage to, personal data".*

As a professional code of conduct, the researcher respected the confidentiality of the data provided and did not disclose it without a legal or academic requirement. Special measures have been employed regarding how the results from the research are communicated with any illustrations involving the locations of existing or potential drug markets being anonymised prior to publication. All research outputs were subject to Metropolitan Police approval prior to publication.

3.1.3 Police recorded crime data

A data sharing agreement was signed with the Metropolitan Police Service (MPS). According to the agreement, drug dealing records were extracted from the Crime Reporting Information System (CRIS) for a two-year period - from 1st April 2009 to 31st March 2011. Overall, 9,318 cases of drug crimes were recorded in the CRIS database for the study area. The incidents were detected from normal police practice and a series of police operations. The latter included four operations which focused on four problematic housing estates in the borough where large suppliers of mainly Class A drugs were identified and offenders arrested. Additionally, there was an on-going police operation with the main objective of arresting at least one drug dealer a day across the borough.

[5] http://www.legislation.gov.uk/ukpga/1998/29/contents [last accessed on 10/05/2013]

Table 1 shows an example of the CRIS data provided by the police. For each incident the following fields of information were available:

- Recorded crime number;
- date of the arrest;
- information on drug types being *possessed*, *supplied* or *produced* at the time of the arrest (all the cases of possession with the intention of to supplying are coded here under the *supply* category);
- location of the arrest with address information and postcode;
- information about the number of people being suspected and accused.

Table 1: Example from the CRIS data

Crime No	GEN Committed on/from Date	CLASS Initial Classification	VEN Address	SUSP Suspect No
4207368	01/04/2009	Sup Cocaine	FLAT A-D,XXX ROAD, LONDON,E3 XXX	1
4207593	30/03/2010	Poss Cannabis	8,XXX STREET, LONDON,E1 XXX	2
4208268	07/04/2010	Prod Cannabis	FLAT 35,XXX HOUSE,XXX STREET,LONDON,E1	1

As is evident from **Table 1** the data include incidents of drug production, possession and supply. The 'address' data details the location where the offender was detected buying, selling or producing drugs. In the case of possession the address represents a public location where a person was seen using drugs, or was stopped and searched and found in possession of them. From the CRIS dataset it was not possible to determine whether a person possessing drugs was a drug dealer or a customer.

3.1.4 Crime data cleaning logistics

Recorded crime data suffer from a variety of issues. For example, not all crime is reported to the police, and when it is, it may be incomplete. In the current study, it is assumed that the crime recording procedure was consistent for all crimes recorded. This is a reasonable assumption as according to police procedures, the supervisor of the crime management unit for every borough in London regularly checks the accuracy of information recorded in CRIS. Despite this, in some cases the information provided lacked full six character postcodes, which prevented the identification of the exact location of the incident. In some cases, the address indicated the street name; but without the full postcode it was impossible to identify exactly on which part of the given street segment the crime occurred. For this reason a decision was made to check and verify every address location in the dataset. In order to be consistent, a special protocol was developed, see **Figure 3**. According to this protocol, only crimes for which the data had an acceptable level of accuracy (i.e. having a full postcode or address), that were located within the boundaries of the borough, and that had occurred between 1st April 2009 and 31st March 2011, were geocoded and used for the research.

Figure 4 shows the data cleaning process. First, incidents were checked to see if they had a full postcode. Where no information was provided for the postcode, where possible, the location was identified based on the full street address and geocoded. If it was impossible to retrieve the geographic location using the street address, the record was excluded from the dataset. Records with full postcodes were instantly geocoded. Geo-coding was accomplished using 'GeoConvert' an online tool developed for UK academics. GeoConvert uses the Ordnance Survey MasterMap® product and has a 0.1 metre address grid resolution. Subsequently, the Easting and Northing coordinates of all point locations were compared using ArcGIS to check that the incidents were located within the official polygon boundaries corresponding to every postcode.

Following this process, there was total of 6,661 records selected for analysis. One issue with the data is that where multiple offenders were included in the same incident, the data contained multiple records for that crime – one for each offender. As the researcher was concerned with crime counts per location, the duplicate records were removed from the data, but the count for suspected field calculated for each line. For example in **Table 2 (a),** four people were suspected of possessing cannabis with the intention of supply, but only one person was accused, thus this was reclassified as one crime incident with four people being suspected and one person being accused, see **Table 2(b)**.

Figure 4: Data cleaning logistics

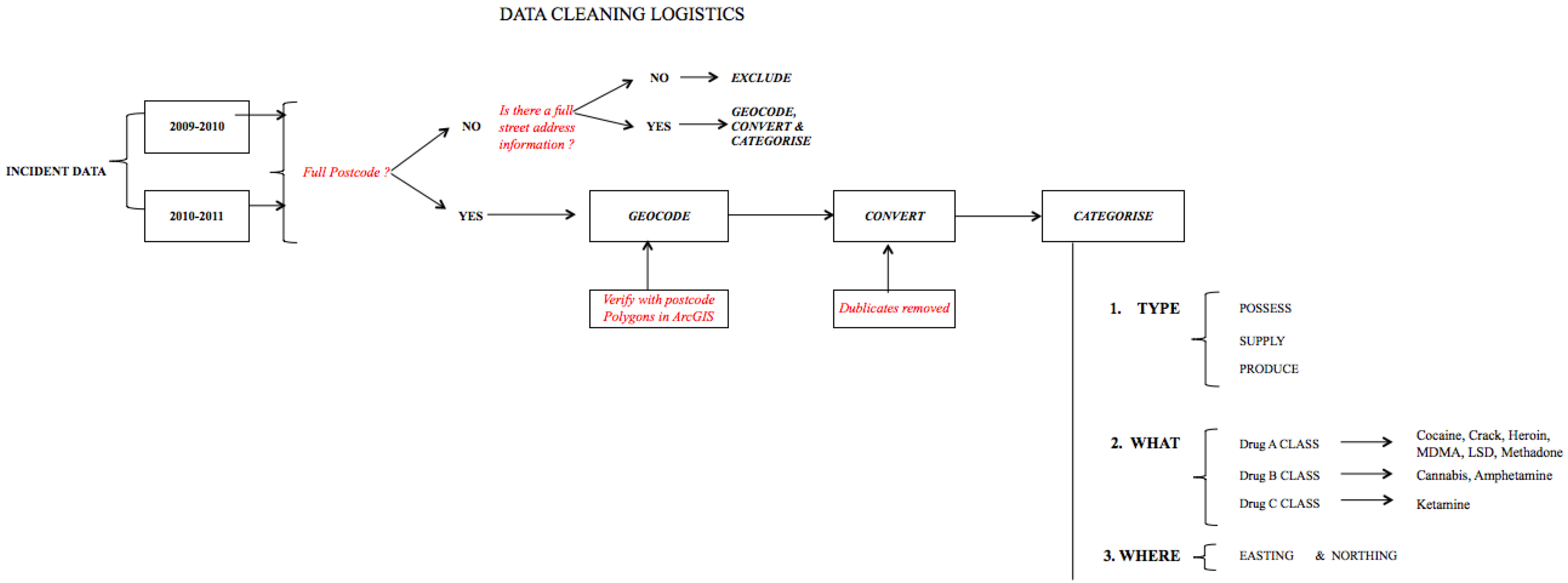


Table 2: a) Crime data classified by offender(s); b) crime data classified by incident

a)

Crime No	GEN Committed on/from Date	CLASS Initial Classification Text	VEN Address	SUSP Suspect No
4200771/10	Cannabis W/I	MILE END ROAD	E1 XXX	1
4200771/10	Cannabis W/I	MILE END ROAD	E1 XXX	2
4200771/10	Cannabis W/I	MILE END ROAD	E1 XXX	3
4200771/10	Cannabis W/I	MILE END ROAD	E1 XXX	4

b)

Crime No	GEN Committed on/from Date	CLASS Initial Classification Text	VEN Address	SUSP Suspect No
4200771/10	Cannabis W/I	MILE END ROAD	E1 XXX	4

The last stage of the data cleaning process was to classify incidents in the following ways:

- Drug *production*, *supply* and *possession* categories. It was hypothesised that these three categories of drug activities would have a different geographical distribution pattern. For example, dealers who supply drugs might be attracted to locations that have or are close to locations with a large number of potential customers moving through the street (see Chapter 5). The definitions for these categories were adopted from Home Office's counting rules (2011) and are defined as follows:
    1. *Production*: 'production or being concerned in the production of a controlled drug' (Misuse of Drugs Act 1971 Sec 4(2)(Police Foundation 1971));
    2. *Supply*: 'supplying a scheduled substance to another person' (Criminal Justice Act 1990 Sec 12). 'Supplying or offering to supply a controlled drug' (Misuse of Drugs Act 1971 Sec 4(3));
    3. *Possession:* 'Possession of a controlled drug with intention to supply or use (Misuse of Drugs Act 1971 Sec 5(3))'.

- Drug class: *Class A* (Cocaine, Crack, Heroin, MDMA, LSD, Methadone); *Class B* (Cannabis, Amphetamine) and *Class C* (Ketamine).

Table 3 shows the final number of incidents that were used in the analysis that follow, separated according to categories of drug supply, production and possession. Overall, there were 734 incidents of drug supply, 93 incidents of drug production and 5,804 incidents of possession. **Figure 5** shows geographical distribution of drug crimes in the borough aggregated to street segments for the purpose of preserving anonymity.

3.1.5 Validation and limitations

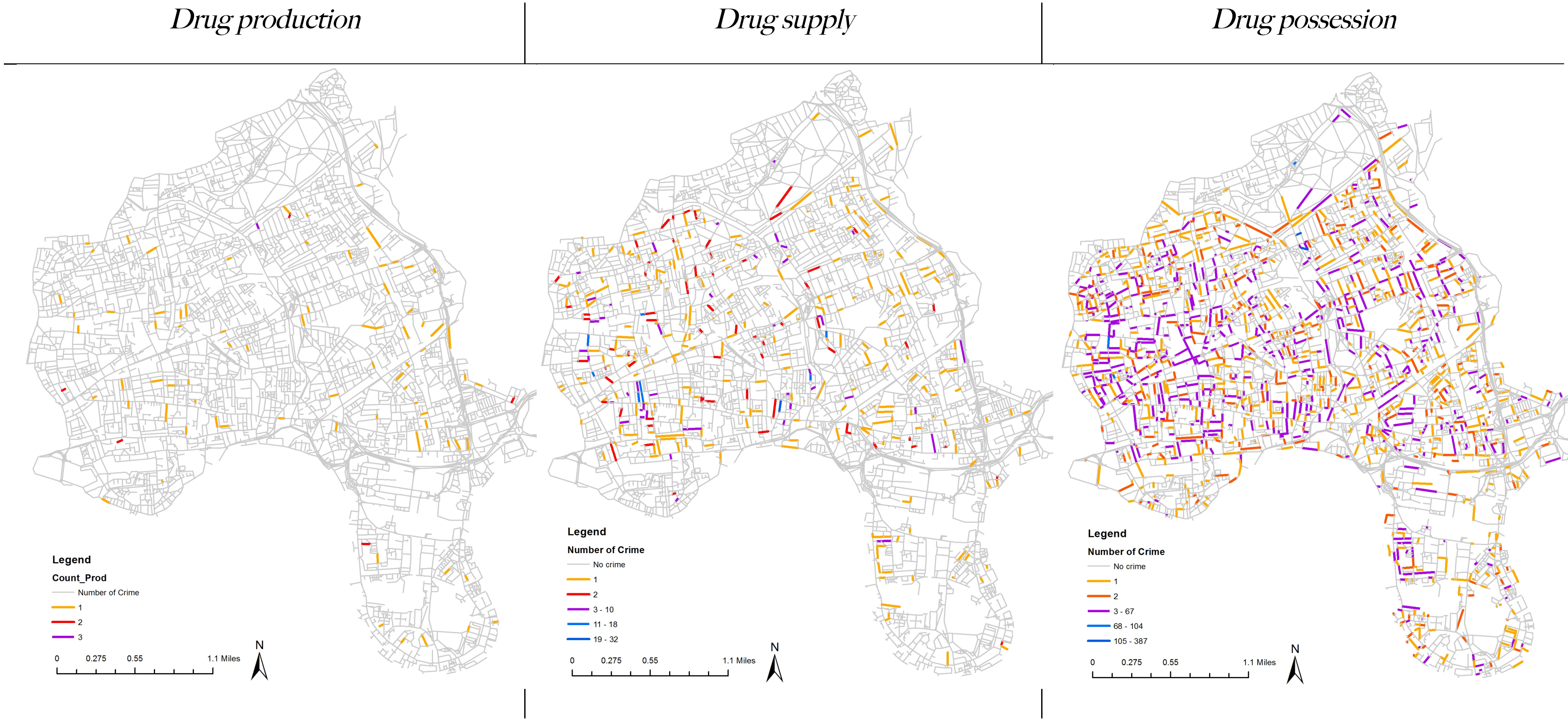
It should be noted that the police recorded data might not prove a complete picture of real crime incidents, since it is not independent of policing strategy and tactics. For instance, the differences in arrest numbers may reflect changes in police patrolling strategies or the changes in police experience of spotting drug dealing behaviour. It is possible that offences are recorded at particular locations, because they are more likely to be detected at them in comparison to all the other places where the dealing occurs, but not detected by police. Consequently, although the drug dealing sample size is quite large (over 9,000 incidents), it is important to note that it is limited only to detected cases, which is a proportion of all drug dealing happening in the borough. Thus, care should be taken during the statistical analysis when interpreting results from a sample to population. As for all studies that use crime records detected by the police, they have some biases (Maxfield and Babbie 2014). In this study, the researcher assumed that these are not systematic and there was no reason to suspect they would be. In fact in a recent study Lammers (2014) showed that the spatial patterns of offenders, detected through investigative efforts vs. those who were undetected, but left DNA traces that could be linked to their offending, were identical. However, the reader should bear this issue in mind.

In this part of the chapter, two of the principal data sources have been described: the case study area and the police crime records. In the next part of the chapter, the appropriate spatial unit of data analysis is established and an initial explorative analysis of geographical trends in the crime data presented.

Table 3: The number of incidents before and after editing the CRIS data

YEAR	CRIS DATA: NUMBER OF RECORDS	EXISTING POSTCODES		CLEARED BY OFFENDER	CLEARED BY INCIDENT	CLASSIFIED BY INCIDENT TYPE			
		FULL POSTCODE	HALF POSTCODE			**SUPPLY**	**PRODUCE**	**POSSESS**	OTHER
1st April 2009 - 31st March 2010	4,268	3,265	999	3,227	3,472	313	46	3,112	***43***
1st April 2010 - 31st March 2011	5,051	3,974	1,074	3,973	3,161	420	46	2,694	***3***
TOTAL	**9,319**	-		**7,200**	**6,611**	***733***	***92***	***5,786***	
						6,611			

Figure 5: The number of drug production, supply and possession incidents aggregated to street segments



3.2. Unit of analysis and data diagnostic methods

3.2.1. Introduction

As discussed, in Chapter 2, as with many crimes, the probability of drug crime occurring at a particular location is not random across the urban fabric, very few locations are well-suited to illegal drug dealing. In line with earlier studies (Eck 1995, Rengert et al. 2005), this research proposes that there are inherent spatial and temporal trends in drug crime occurrences. First, it is expected that drug incidents do not occur in a completely random manner and that offences will cluster in space (**Table 4,** hypothesis N1). Second, it is expected that depending on the drug crime type – *drug production*, *drug supply* or *drug possession* – the spatial clusters of crime will vary considerably, reflecting the distinctive spatial logics associated with each type of drug crime type (**Table 4,** hypothesis N2). For instance, it is anticipated that the distribution of drug supply incidents will be different to that for drug production incidents. This is because, the aim of the drug dealer is to supply product(s) to drug users, and hence it makes sense for them to operate near more accessible locations that attract a large number of potential clients (Eck 1995). In contrast, the drug production process involves making and allocating large quantities of drugs. Thus, the primary function of drug production crime is to stay unnoticed, potentially be reasonably well accessible to other drug suppliers and have a good access to highways or main roads (Rengert et al. 2005). The drug possession cases most likely to be associated with locations where the use of the illicit drug will more likely not to be noticed by public authorities, at places such as parks and not busy areas.

Table 4: List of hypotheses to be tested in this chapter

N	Hypothesis
1	The observed geographical clustering of drug crime data has not occurred in complete spatial randomness
2	The geographical distribution of drug supply incidents will be dissimilar to geographical patterns for drug production and drug possession

In the next section, the spatial unit of data analysis used to explore hypothesis is defined and the methods for exploratory data analysis are presented.

3.2.2 The unit of analysis

Understanding the effect of the urban environment on the occurrence of crime, involves defining the spatial setting where the latter occurs. Methodologically, the procedure of defining the spatial setting involves identifying the geographical boundaries of the *spatial unit* where the crime took place. Depending on the type of available crime data and a researchers understanding of the interaction between crime and environment, the spatial *unit of analysis* will vary in scale from citywide to local micro scale. Different units of analysis have been used in different studies, ranging from large areas, such as UK census, lower super output areas (LSOAs), small neighbourhoods, to street segments, to incident point locations.

Depending on the unit of aggregation, several potential errors might be encountered in interpreting crime distribution across a study area.

The first error relates to the *size* of the unit and varying the *boundary* of aggregation, and is termed *modifiable area unit problem* (MUAP, Openshaw 1984). Depending on the level of geography (country, city wide, neighbourhood scale, etc.), there will be a considerable variation in the notional boundaries of the spatial unit. Consequently, the aggregate totals of crime will fluctuate between two maps with different spatial units of aggregation. This will make the interpretation of real crime distribution misleading. Importantly, with larger spatial units of analysis, it is problematic to hold the assumption that the aggregate counts reflect adequate representation of discrete acts of crime in relation to urban setting.

An inappropriate spatial unit of analysis can also lead to misleading conclusions regarding the relationship between crime and the spatial setting. This type of error is termed the *ecological fallacy* (Robinson 1950). An example could be the assumption that all streets have the same crime risk in the area, without considering that the streets might vary in their spatial settings. Or similarly examining aggregate crime counts at the electoral spatial unit of aggregation without considering the local variability of spatial settings.

Given the methodological challenges mentioned above, many researchers (Weisburd, Bernasco and Bruinsma 2009, Brantingham et al 2009; Groff, Weisburd and Morris 2009) have emphasised the benefits of using smaller unit of analysis, such as the street block or event point level in crime analysis. These small units tend to have more homogeneous spatial nature, which overruns the issues discussed. For instance, in a single street block the house typology will not change dramatically, however, it will vary from street to street. Recent research (Andersen and Malleson 2013) on the evaluation of different spatial units of crime data aggregation showed that on the larger scale, such as census tracts and census blocks, the distribution of crime patterns within these large units was similar. However, at the street segment level, crime patterns were less uniformly distributed across the study area. The study concluded that a small number of crime prone streets affect the total volume of crime in the area. Hence, a small spatial scale is more suitable in representing the aggregate pattern of individual acts of crime.

3.2.3 Street segment as a unit of analysis

In this research the *street segment* was selected as the principal unit for crime data analysis. It is defined as a line that represents two street blocks facing each other and being located between two street junctions, see **Figure 5**.

Figure 5: The definition of the street segment unit from the street block

This unit of analysis was chosen for the following methodological and theoretical reasons.

a) It is the smallest urban block that retains the integrity of the unit place. Unlike an administrative ward or census tracks, street segments have clear recognisable boundaries, which allows identification of the variability of crime among small geographical areas and their relationship one to another. Moreover, unlike address point data, it minimises the risk of including miscoded data into the analysis. Hence, this is a desirable unit of analysis since it prevents unnecessary errors both in concealing spatial crime trends and including miscoding.
b) A street segment is a suitable unit of analysis since it captures the behavioural settings where human interaction occurs. It is commonly acknowledged as a spatial unit that organises daily life (Jacobs 1961; Hillier and Hanson 1983), because it captures visitors passing by, people working on the block and residents interacting and moving across the block. The presence of mixed land uses additionally increases the encounter and interaction on the segment.
c) Many things influence peoples' movement choices, to include individual goals, land uses, public transport infrastructure and more. They are also likely be influenced by the spatial arrangement of the urban street network (Hillier and Hanson 1984). If this is so, then crime as a social activity need not be an

exception and hence its patterning may also be influenced by the street network. Scholars propose (Hillier and Shu 2000; Hillier and Shahbaze 2005) that street network layout and the way people use it has an important effect on the geographical variability of crime incidents. Hence, in this research it was assumed that both drug dealers and buyers navigate, meet and engage in drug transaction across the street segments.

Previous studies on drug crime have identified the street network as equally sized blocks with an approximation to the layout of the real street network (Rengert et al. 2005). Since the aim of this research is to examine spatial patterning of drug crime in relation to movement flows and land uses, the main objective is to capture the real arrangement of the street network as much as possible. Thus, in this research the size of the street segment unit follows the arrangement and layout of the real street network of the case study area. The total length of the street network considered is 507 km and it consists of 6,756 street segments that consequently became the units of analysis. The segments had an average length of 75m (the longest segment was 982m long). Statistically this variation in street segment length will affect the number of crimes assigned to the segment where probabilistically the longer the segment the higher the chance of drug crime per metre length. In order to account for this variation, segment length is included as an independent variable in the spatial regression models that follow (for the detailed description see Chapter 5). However, before presenting this regression analysis, to provide some context , Exploratory Data Analysis (EDA) is used to examine general patterns of drug crime in the study area. The next section details the EDA methods.

3.2.4 EDA diagnostic methods

In general, spatial statistics are concerned with quantifying and analysing geographical data using three spatial concepts: the notion of *distance*,*adjacency* and *interaction*. The measure of ***distance*** signifies the geographical separation between two or more crime points. It is usually expressed in metres and is a continuous variable. In this research, two different quantifications of distance are used – Euclidean and network based. The Euclidean or direct distance measures the geographical separation by constructing an abstract straight line between two locations. The network distance is constrained by the street network geometry. Thus, it represents the distance between two points of the shortest, physically accessible travel route. Commonly, this distance is longer than the Euclidean distance; however, it is a more realistic quantification of distance, especially for measuring movement or routes through urban settings.

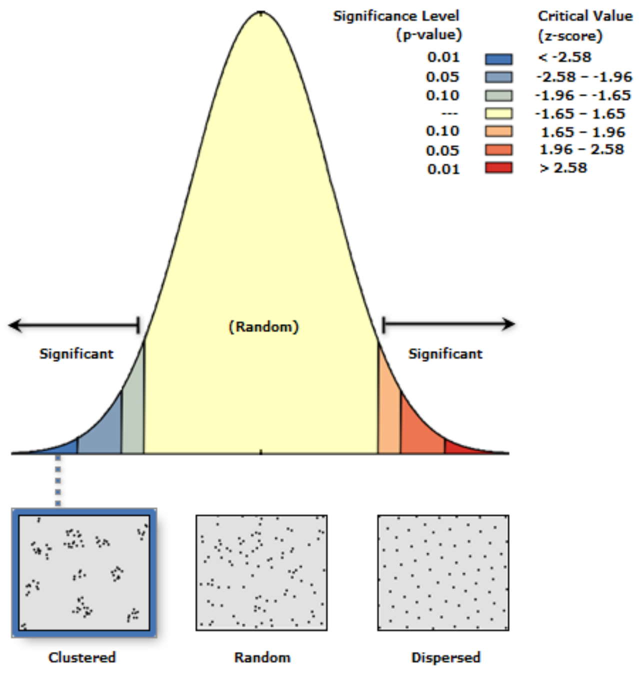
In crime analysis, the concept of ***adjacency*** is used to identify the 1^{st}, 2^{nd} up to n^{th} nearest crime locations for a given crime point. Thus, it gives an indication of how many near neighbours a single location has. Additionally, the adjacency concept is used for testing how similar or dissimilar the frequency values of crime are at nearby locations. This allows the identification of the concentration of crime with similar frequencies. The adjacency concepts combined with distance measure can be used to show how dispersed or clustered crime points are across the case study area.

The last spatial concept refers to the notion of **interaction**. It is theorized that the strength of relationship between events depends on how geographically close those events are to each other (Tobler 1970). It is expressed as an inverse function of distance. Thus, nearby locations influence each other more than do locations that are more distant.

A common way of understanding the processes underlying the spatial dependency of crime is through the analysis of crime patterns. There are various statistical tests that measure crime patterns for different units of analysis. Here, three methods of Explorative Data Analysis are used, which are described in detail below.

The first EDA analysis quantifies the point pattern distribution of drug crime events. According to Hypothesis N1 (**Table 4**), it is expected that the drug dealing point locations should have non random distribution on the geographical surface. Using *Average Nearest Neighbour* (ANN) test the assumption of *complete spatial randomness* (CRS) of crime points is tested. The CRS assumption states that the observed arrangement of crime locations on the geographical surface represents only one version from all those according to random spatial process. That is CRS hypothesis claims that the same number of points with fixed values (i.e. number of drug dealing incidents per location) could have an infinite number of different spatial arrangements and that the precise patterning is purely random. **Figure 6** illustrates a theoretical distribution of possible arrangements spread across a geographical surface. Here, the majority of all point arrangements (approximetly 95%) have clearly random spatial distribution. In only very rare cases (less than 5%) does the distribution of points appear to either be geographically clustered, or to be equally dispersed on the surface. That is, the probability of this type of arrangement is very unlikely to be produced by random spatial process. Thus, if the observed point pattern shows a significantly clustered or dispersed arrangement with small probability value (*<0.01*), the CRS hypothesis can be rejected with 99% confidence, because it is highly unlikely that the observed point pattern was generated as the result of random spatial process.

Figure 6: Average Nearest Neighbour (ANN) test



(*Source:* the graphic is obtained from HTML report file produced by ArcGIS software. ESRI 2012, ArcGIS Desktop: Release 10. 1; Redlands, CA: Environmental Systems Research Institute.)

The ANN tests the CRS hypothesis by computing the spatial relationship between discrete point locations. The spatial relationship is defined through the concept of *adjacency* combined with the *distance* measure. This gives an indicator of how many nearest neighbours a single crime location has. The ANN is defined as a ratio of the *observed* nearest neighbour distance to the mean *expected*, assuming a random distribution, see **Equation 1**,

$$ANN = \frac{\overline{D}_O}{\overline{D}_E} \tag{1}$$

where $\overline{D}_O$ is the mean distance of all *observed* crime points and their respective nearest neighbours. It is computed from the sum of distances d_i between point *i* and its nearest point and is divided by the total number *n* of observed points, see **Equation 2**,

$$\overline{D}_O = \frac{\sum_{i=1}^{n} d_i}{n} \tag{2}$$

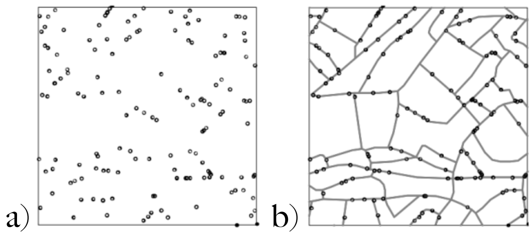
and $\overline{D}_E$ is the *expected* mean distance for the points given a random distribution pattern in the study area *A*, see **Equation 3**.

$$\overline{D}_E = \frac{0.5}{\sqrt{n/A}} \tag{3}$$

This ratio (3.1) shows how dispersed or clustered the points are. For this index, a value less than 1 indicates spatial clustering. This should occur if the observed crime points are closer to each other than expected by a random geographical distribution of points. An index greater than 1 indicates that the points are more scattered than expected by chance. If the ratio is equal to or close to 1, this means that the crime points are randomly distributed across the study area. Thus, other non-spatial factors may influence the occurrence of crime. The test also outputs a Z-score and p-value for the corresponding ratio, to enable hypothesis testing.

The ANN test is based on the assumption that the observed crime points are both independent from each other and can be located anywhere on the surface. However, in reality the crime points are bounded by the geography of the setting, thus they can not appear anywhere on the surface. Moreover, depending on the surface in relation to which the crime points are examined, the assumption of non-random arrangement of points might not bepossible. It has been argued (Okabe and Sugihara 2012) that when analysing events that occur on the street network , traditional geographical analysis that uses *Euclidean* distance (i.e. as the crow flies) to identify the spread of neighbouring points, is not methodologically accurate. This is because when the street network is considered, the adjacent relationship between two crime points is determined by the shortest path on the network not the shortest Euclidean distance. Thus, it might appear that the crime points are clustered or dispersed on the geographical surface, but on the street network surface the same arrangement might be the result of a random point distribution, see **Figure 7**. That is a street network may impose a non-random pattern.

Figure 7: The same point pattern arrangement on a Euclidean plane (a) and on a street network (b)



(Source: Okabe and Sugihara 2012)

Scholars suggest (Okabe and Sugihara 2012) that the CRS hypothesis should be tested by analysing the arrangement of points using *a network nearest neighbour distance*. The advantage of the test is that it incorporates the street network in the computation of the expected distribution. Similar to Euclidean ANN test, a ratio is calculated; where the shortest path between observed points on the network is compared to points that are randomly generated on the same network, see **Equation 4**.

$$I_G = \frac{1}{\mu}\frac{\sum_{i=1}^{n} d_s(p_i, p_i^*)}{n} \quad (4)$$

This is a modification of the Clark-Evans index (Clarke and Evans 1954) formulated for the network (for the detailed mathematical description see Okabe and Sugihara 2012). Here I_G index shows the ratio of mean nearest neighbour network distance $d_s(p_i, p_i^*)$ divided by the mean expected value μ, given a random distribution of points across the street network. The final output from the test shows the distribution of the cumulative number of point locations plotted against the network distance, where the observed curve is compared to the 95% confidence interval of lower and upper significant values produced by Monte Carlo simulation. Points are considered to be clustered on a network if the observed distance between neighbouring points is shorter than the nearest neighbour distance obtained for random distributions of points. In this research, this method of ANN estimation is used to test Hypothesis N1. The method was tested using SANET version 4.1 software (Okabe et al. 2006).

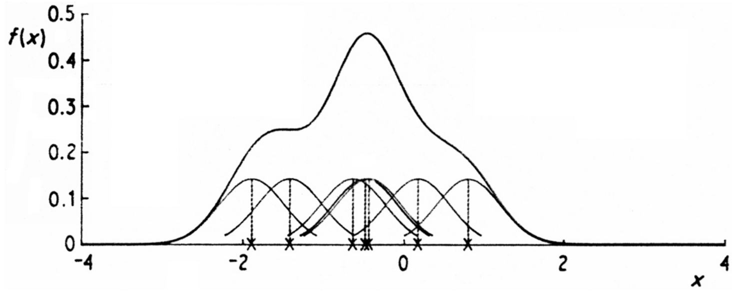
In order to visually identify where crime is concentrated in the city, the second EDA method identifies crime clusters on a map using a Kernel Density Estimation (KDE) method. For the n number of observations, the KDE method $\widehat{f_h}(x)$ estimates the density value $f(x)$ at point x as:

$$\widehat{f_h}(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x_i - x}{h}\right) \tag{5}$$

where K is the kernel function in this research defined as quadratic kernel function (Silverman 1986, p 76, equation 4.5) and h is for the bandwidth. The kernel function interpolates each crime incident value to the entire area by evaluating the distance between locations, where the highest value is at the crime location and with the increase in distance away from the given location the value decreases up to 0, at the search distance specified by the bandwidth. The overall density distribution is a cumulative density estimate that incorporates all individual kernel density estimates at every location (see **Figure 8**). The final output map shows a continuous area with crime count densities layered on top of each other and coloured from red to blue shades, denoted for high and low cumulative crime density values accordingly.

The Kernel Density analysis is obtained using ArcGIS version 10.1 software (Esri Inc. 1992-2012; McCoy 2004).

Fugure 8: Kernel density estimation (Source: Silverman 1986)



The third EDA analysis looks at the distribution of crime *frequency* values at the small areal level, to see if there is an interaction between adjacent crime values. For instance, locations that have higher than average frequencies of drug dealing occurrences might be clustered together and potentially form an illicit drug market. In geography, such pattern is known as *spatial autocorrelation* and is statistically analysed using *correlation analysis* (when variable is correlated for adjacent units) or *probabilities* (the likelihood of an event occurring in the area, given the existence of a similar event in a nearby area) or *similarities* (the degree of similarity (dissimilarity) of an event in neighbouring areas). Here, the latter definition of autocorrelation is used to perform the Moran's I statistics (Anselin 1995).

This test shows how similar or dissimilar the frequency values of crime are for neighbouring geographical areas. For this test, crime points are aggregated to predefined spatial units and spatial autocorrelation analysis performed. For this test, nearby units are compared to see if there is evidence of clustering of similar values, *see* **Equation 6**.

$$I = \frac{N \sum_i \sum_j w_{ij}(x_i - \mathrm{X})(x_j - \mathrm{X})}{(\sum_i \sum_j w_{ij}) \sum_i (x_i - \mathrm{X})^2} \qquad (6)$$

The Moran's I is calculated according to the ratio, where the difference between the crime intensity value (Z_i) at location *i* and the mean for all crime intensities (Z) is divided by the variance (S_z) across all observations. The *neighbouring* concept is defined according to weighted measure of inverse distance decay (W_{ij}) between observations *i* and *j*, where the area is considered to be a neighbour, if it is within a threshold distance from a given area and a non-neighbour if it is further away. The results from the test show either positive spatial interaction (neighbouring segments have similar crime frequencies), or negative spatial interactions (segments with dissimilar frequencies clustered together).

Similar to Hypothesis N1, this hypothesis was tested assuming that crime points are constrained by the street network. Thus, the neighbouring concept for the observations *i* and *j* is defined (Yamada and Thill, 2007) through the street network connectivity value, where two streets are assumed to be neighbours if they share an intersection or node. Thus, the test determines if the crime intensity at each street segment is significantly autocorrelated to that of neighbouring segments. In addition to computing a global index of clustering, the local Moran's I statistics (analysed in GeoDaNet software; GeoDa Center 2013 (Anselin et al. 2006; Hwang and Winslow 2012)) provides am index of clustering at the local level that allows patterns to be identified more precisely. For example, which street segments exactly have high levels of crime and are adjacent to other segments with high frequency of crime.

The next part illustrates all the results obtained from the EDA tests.

3.4. General spatial trends of drug crime data

To establish a general understanding of how drug crime is distributed geographically across the case study area, the hypotheses from **Table 4** are tested using EDA diagnostic tests. This allowed the identification of local clusters of crime nested within the larger geographical context and provided verification that the street segment scale is a suitable unit of analysis for the given dataset. The following sections describe this in detail.

3.4.1. Geographical clustering of drug crime incidents

Table 5 presents the ANN ratio for the three drug crime types (*production, supply* and *possession).* Based on the p-values the CRS hypothesis is rejected in all cases. For each type of crime, the ANN index is less than 1, which means that the incidents were more clustered or geographically nearer to each other than would be expected by random distribution. However, as discussed above, crime might appear to be clustered when they are measured using Euclidean distance, not be when account is taken of the street network. To check if the crime incidents were non-randomly distributed across the street network layout, a second nearest neighbour analysis was performed where the crime incidents were measured according to street network distance.

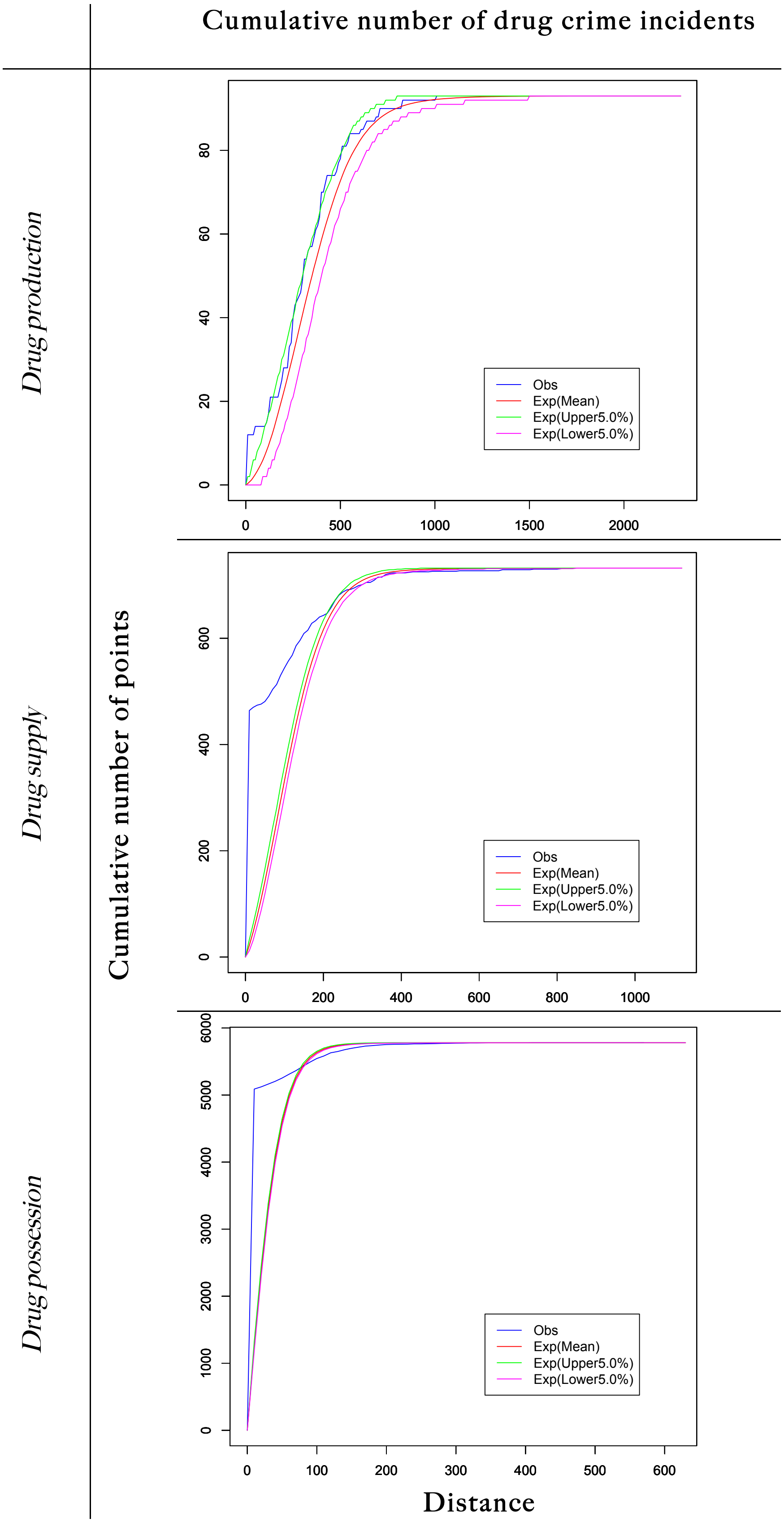
Table 5: Summary of observed and expected Average Nearest Neighbour index using Euclidean distance

Drug crime type	Observed mean distance	Expected mean distance	ANN index	z-score	p-value
Production	197.96	268.21	0.73	-4.80	<. 01
Supply	40.15	100.3	0.400	-31.04	<. 01
Possession	7.38	37.03	0.199	-116.24	<. 01

Figure 9 illustrates the cumulative number of drug crime points plotted against network distance. The observed curve (coloured blue) is shown in relation to the 95%

confidence intervals computed for the expected distribution. It can be seen that drug production locations appeared to be randomly distributed across the street network. However, there is evidence of significant clustering for drug supply and drug possession incidents up to 200 and 100 metres along the street network respectively, which approximately corresponds to less than 3 minutes walking distance between the incidents.

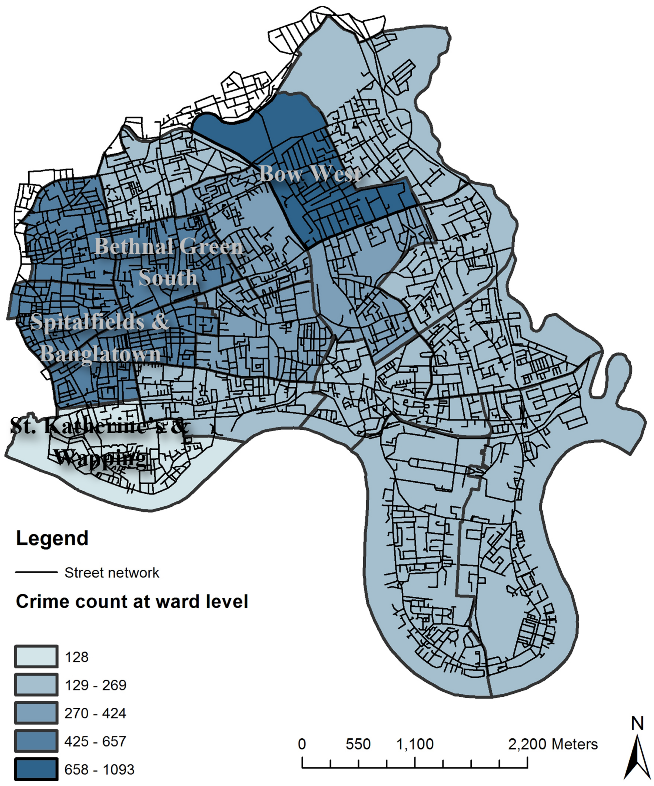
Figure 9: Observed and expected nearest neighbour curves for ***production*** (n = 92), ***supply*** (n = 733) and ***possession*** (n = 5,786) drug crime calculated using shortest network distance



3.4.2 Geographical patterning of drug production, supply and possession crime

Having established that drug crimes are clustered, to visually identify the clusters in the borough, the incidents are first aggregated according to administrative ward divisions. The official geographical boundaries were obtained from the Ordnance Survey. The **Figure 10** shows that even at such a large scale of aggregation, the distribution of drug crime events is skewed towards some locations where the aggregate number of incidents is nearly 5 times more than in other parts of the borough. Namely, the Bow West ward had the highest count of drug crime (n = 1,093) across the borough and the St. Katherine's & Wapping riverside area had the lowest count (n = 204). Although geographically the park is located on the north part of the Bow West ward, due to the high level of data aggregation the entire area appeared to be a drug prone zone. Furthermore, in **Figure 10** several geographically neighbouring wards had similar crime counts, for instance, the Spitalfields & Banglatown and Bethnal Green South wards that share the Brick Lane and Shoreditch recreational neighbourhoods.

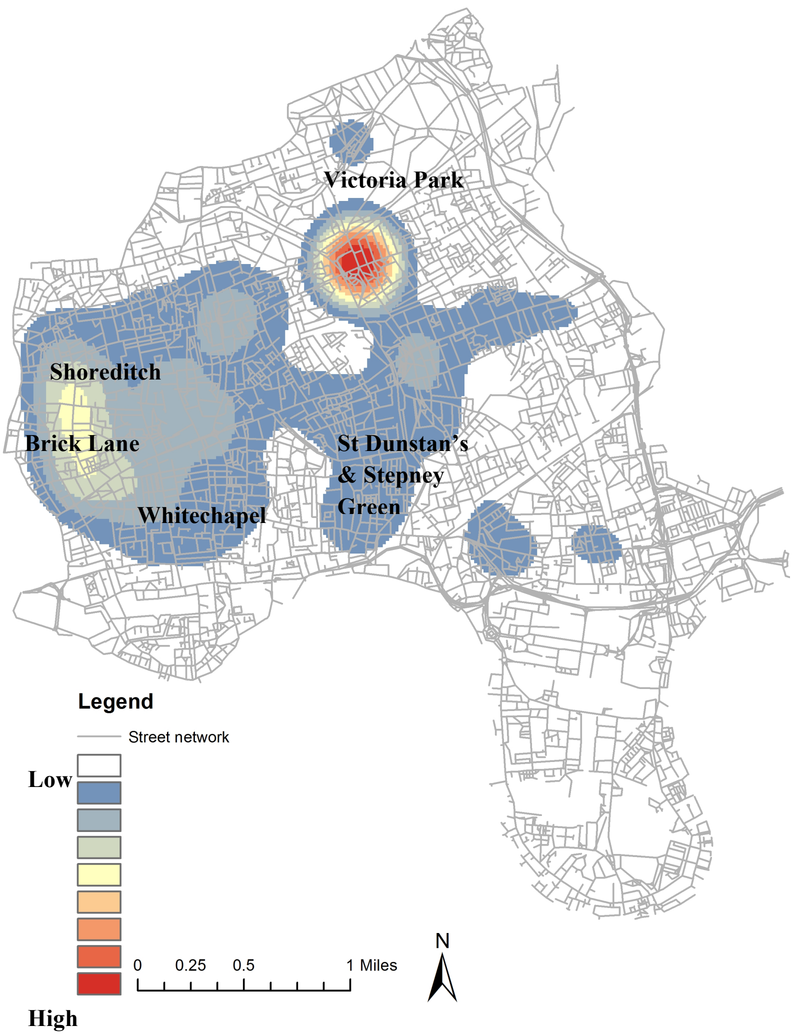
Figure 10: Aggregate count of drug crime (n= 6,611) in Tower Hamlets according to administrative wards of the borough; thematic classes were generated according to a *natural break* distribution



Although, this level of analysis suggests an uneven distribution of crime incidents, it is hard to depict the underling pattern of crime, because all locations within the predefined areas are treated equally similar in relation to crime activity (ecological fallacy). Thus, it causes neighbourhoods to appear spatially homogeneous with regard to criminal activity and the actual drug crime concentration remains masked at this large scale of data aggregation

In order to better examine the spatial distribution within wards, the same crime data were mapped using a Kernel Density Estimation method. **Figure 11** shows a slightly different pattern in comparison to **Figure 10**. Here, two clusters with a high concentration of drug crime can be identified near Victoria Park and the Brick Lane area.

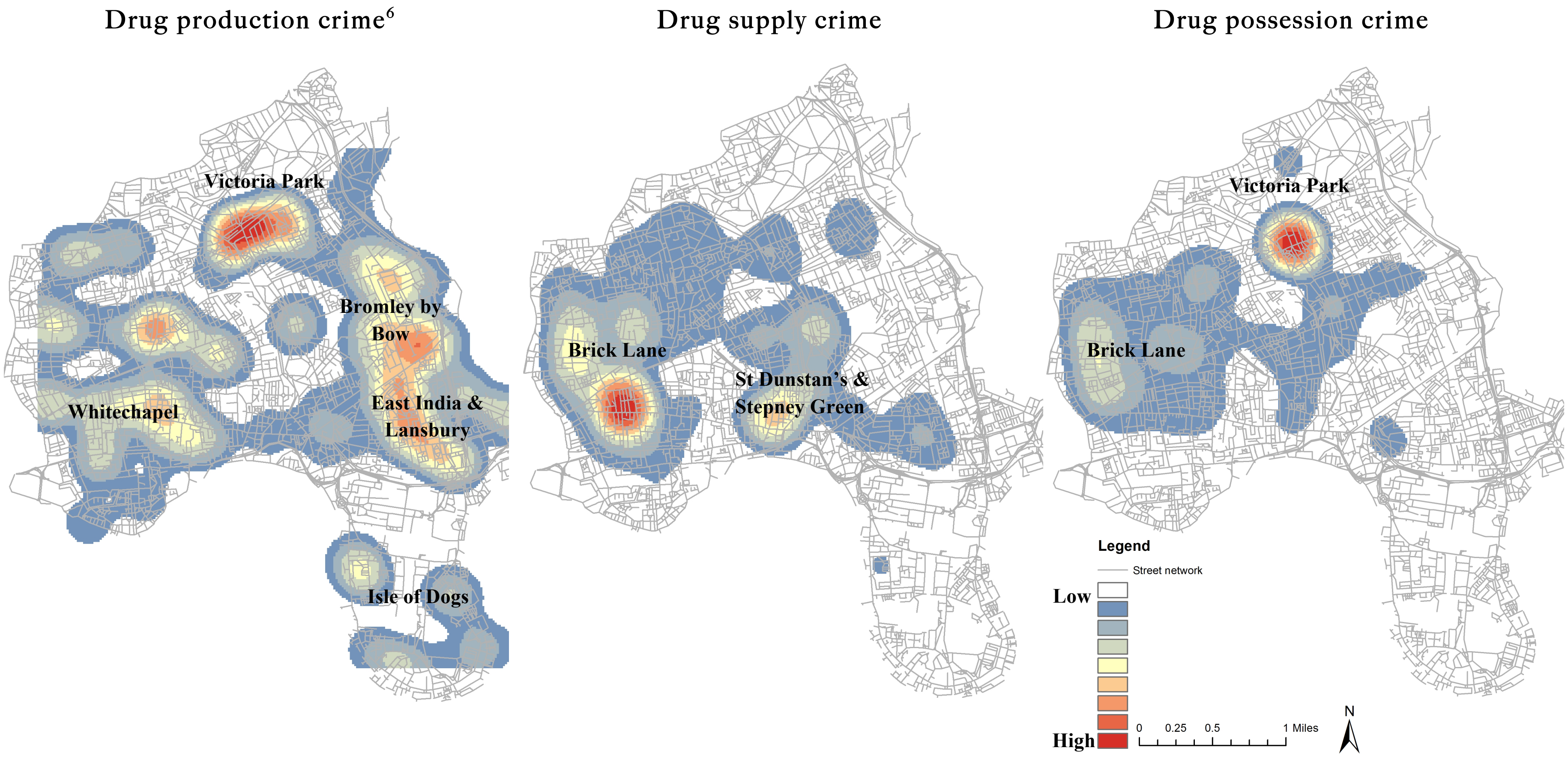
Figure 11: Kernel density map of drug crime (n = 6,611) in Tower Hamlets borough; the counts are obtained from *natural break* distribution.



At this point, it should be reiterated that both **Figure 10** and **Figure 11** show all crime occurrences with no distinction made between drug crime *production*, *supply* or *possession*. When these data are disaggregated by crime categories, it is evident that the spatial patterns differ. The Kernel density map in the **Figure 12** demonstrates this clearly (also see, **Appendix 1-3**). There is a high concentration of drug production crime in the east part of the borough, whereas for drug supply and possession there is a high concentration of incidents near Brick Lane, the Whitechapel and Stepney Green areas.

Overall, the kernel density maps illustrated a great "patchiness" of drug crime across the borough and that the geographical distribution of crime varies between categories. Although the maps identify the areas of high drug crime concentration, the method fails to explain *why* these areas attract such a level of crime. The next section examines drug crime in relation to street segments in greater detail.

Figure 12: Kernel density maps of drug ***production*** (n = 92), ***supply*** (n = 733) and ***possession*** (n = 5,786) crime in Tower Hamlets borough, counts are obtained from *natural break* distribution



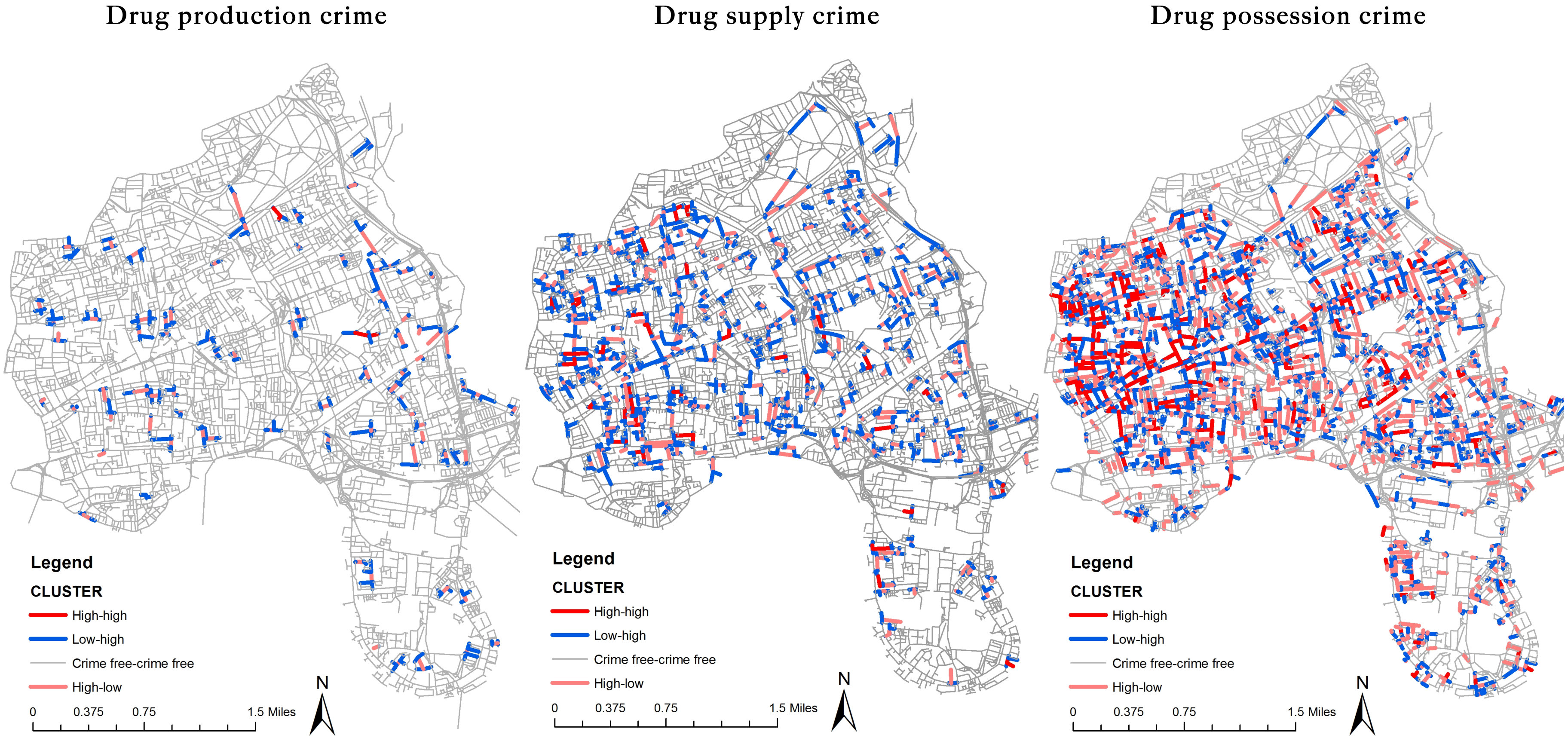
[6] The cut off on the map demonstrates the edge effect

3.4.3 Geographical interaction of drug crime incidents

Although the ANN test showed significant spatial clustering of drug crime, it did not show the degree of spatial variability of drug crime across the street network. That is, whether the street segments with similar frequencies of drug crime are clustered together or not. This issue is now explored using an autocorrelation test. **Figure 13** shows whether the frequency of crime on a given segment is similar or dissimilar to that on nearby streets. Only those segments are presented that are statistically significant in relation to neighbouring segments. If the occurrences of drug crime are similar for the two neighbouring segments than the two are positively spatially autocorrelated. If it is significantly different to that on adjacent streets, the street segments are negatively spatially correlated. In **Figure 13** the street segments coloured red colour are those that have a high frequency of drug crime and that are adjacent to high crime street segments. Segments coloured with pink are those for which adjacent street has a higher frequency of crime than the given segment. Blue coloured segments are those that have low crime counts themselves, but that are located near segments with high or moderate frequency of crime. The segments that both do not have crime and are not located near the crime prone segments are coloured grey.

First, it can be seen that similar to kernel density maps, at the street segment level the distribution of drug crime for different categories of crime varies considerably. Drug production crime is more concentrated in the eastern part of the borough, in comparison to drug supply and possession crimes that have a noticeable concentration of red colour segments in the west end part of the borough. A positive autocorrelation can be observed in some areas in the borough, where there are high crime streets surrounded by other high crime streets. However, there are also many examples of negative autocorrelation, whereby low crime streets are adjacent to high crime streets. These patterns implicitly indicate that the street network arrangement might have an important influence on the likelihood of drug crime incidents.

Figure 13: Moran’s I test with weights according to neighbouring street segments up to 1 connection



Conclusion

The initial analysis of the spatial pattern of drug crime data suggests that this type of crime is not randomly distributed across the case study area. At least 3 minutes walking distance away from every incident another drug supply or possession incident can be located. It is also apparent that the different types of drug crime have different spatial distributions, as expected. Thus, dissimilar characteristics might influence different types of drug crime. Consequently, in the subsequent chapters, the three types of drug crime are treated as three separate dependent variables and the same analysis is repeated for all of them.

For the descriptive analysis, drug crime events were aggregated to two different spatial units of analysis – administrative wards and street segments. However, given that there appear to be clear differences in risk even for adjacent segments, it is evident that the street segment is a more suitable unit of analysis for the research that follows.

In the subsequent empirical chapters, the crime data are examined using the street segment as the unit of anlaysis. It not only minimises arbitarary boundary selection, but produces more homogenous units, while increasing the variance between segments. Additionally, there is a strong theoretical reason for analysing patterns at this level, since it defines the behavioural settings where dealing takes place. It is believed that this unit of analysis will contibut towards a better understanding of the drug crime problem.

In order to examine the influence of street network and its layout on the location of drug crime, the following chapters will examine crime in relation to different spatial properties of the network– by looking at the type of the road, connectivity, and land use distribution. The analysis will employ the Space Syntax technique to derive street network measures of permeability. Before proceeding to the main empirical chapters, the Space Syntax technique is detailed in the next chapter.

CHAPTER 4:

Street network analysis introduced

Introduction

In Environmental Criminology it has been suggested that *"crime is strongly related to aggregate elements of the perceived physical environment: nodes, paths, edges and an environmental backcloth"* (Brantingham and Brantingham 1993; p. 3). These scholars have found (Bevis and Nutter 1977; Groff and Lockwood 2014) a strong relationship between street network layout complexity and crime. It has been argued (Brantingham and Brantingham 1993) that when examining the geographical pattern of crime all streets, roads and pathways should be included in the analysis. Thus, it can be suggested that in order to examine the "environmental backcloth" in relation to crime, the entire street network should be included into the analysis as a separate independent variable.

In order to model the urban network as an infrastructure where urban movemement flows occur, this research employs a technique first developed in the field of architecture that analyses movement flows in the city. The Space Syntax technique (Hillier and Hanson 1983; Hillier 2007) conceptualises the street network layout into a relational graph, where the probabilistic volume of movement is calculated using topological metrics, rather than metric distances or the administrative categorisation of streets. The technique allows a systematic and objective estimation of movement flows, since its conclusions are based on the examination of the actual pattern of connections of the street network.

In this chapter, a general introduction into current knowledge on street networks and their properties is presented, followed by an introduction to the main concepts and methods of spatial patterns of Space Syntax. This method is employed in the subsequent Chapters 5, 6, and 7 to examine drug crime in the city.

4.1 Urban street network

One of the principal functions of the urban street network is to accommodate different types of movement, such as pedestrian, bicycle and vehicular and providing constant communication between all geographical destinations that the street network covers in the city. Additionally, the urban street system facilitates the social and economic organisation of the city (Jacobs 1961, Hillier and Hanson 1983). By accommodating and maximising the movement and occupancy of urban spaces, the street network facilitates the distribution of housing and different land-usages across the city. For instance, commercial land uses will tend to be located on or near busy streets and housing estates will be on quieter street network segments (Hillier and Hanson 1983; Hillier 1996).

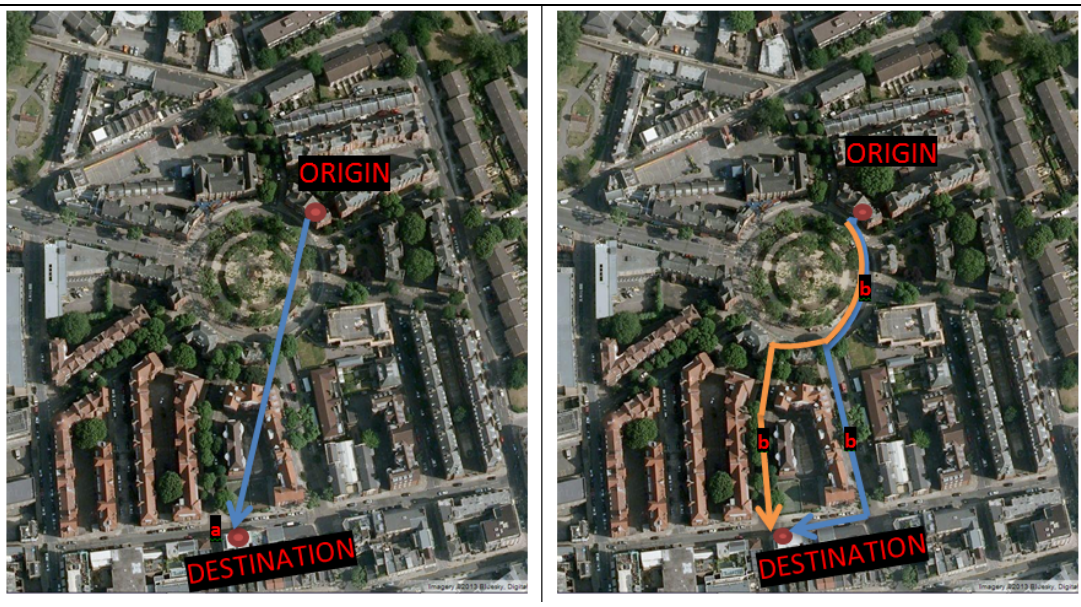
Although the street network is much more than a system that provides communication (Hillier and Vaughan 2007), at a more inherent level it still caters for movement. In order to provide a constant flow of movement in different directions, the street network should be *continuous* in its structure. That is, all streets should be interconnected into a contiguous network regardless of their type (major street, high street, residential street, private road and more) or movement type that they accommodate. Urban researchers (Hillier and Hanson 1983) have claimed that the *continuity* of the street network is the most inherent property of the network system, since it provides movement circulation between many origins and destinations from local neighbourhood to city wide scale. Moreover, this property of the street network allows movement across the city in two principal ways:

- *movement to* a place, when a *destination* is selected from the origin;
- *movement through* a place, when a *route* is selected involving a corresponding sequence of places to be visited or passed through during the trip from the origin to destination (Hillier and Iida 2005).

So, a local high street will be a destination to visit and the street segments that are passed through during the journey to it will be referred to as places used for ‘movement through’, see **Figure 1**. It has been proposed (Hillier 1996) that every street segment of the street network can act as both a destination to visit and a space to pass through. Subsequently, the number of destinations or *to-movement spaces* is more constant across the street network, in comparison to both the number and sequence of through-movement spaces. The latter increase exponentially with longer journeys, but tend to approximate to a straight line.

Figure 1: Two ways of movement through the street network: to-movement space (a); through movement space (b)

Movement *to* a space | Movement *through* a space



Picture is adapted from Google Maps image.

Although the street network caters for movement circulation, the actual distribution of movement densities is not uniform across the urban grid. Research in urban studies (Hillier 2007) suggests that people tend to select nearby destinations more often than destinations that are farther away. Moreover, given that activity places are not uniformly distributed across the city, and have a bias towards areas of high concentration of activities and major transportation nodes, over the course of time some places are visited much more than others in the city. Depending on the scale of movement, or how far apart the origin and destination are, more intermediate segments will be passed through and potentially more route choices will be available. So, on average some streets will experience more movement passing through than others, due to simply being strategically positioned in the street network layout (Hillier and Hanson, 1983).

The unequal distribution of movement volumes across the street network is believed to be associated with the level of *permeability* (Hillier and Hanson, 1983). This is a positive attribute of the street network, since it indicates the degree to which both street network layout and urban form permit physical movement and facilitate access to a selected destination. Depending on the type of movement (pedestrian, vehicular, public transport) and scale of journey (local, regional) the street attributes of permeability will vary. For example, for pedestrian trips made to a local high-street from adjacent neighbourhoods, permeability is associated with the local design of street connections that facilitate the shortest or easiest route to the high street. Scholars (Hillier 2007) have suggested that at the very local scale permeability reflects people's judgment about the metric distance between an origin and destination. In the case of the trips made at the city scale (for instance, from home to work), the large-scale street layout geometry and the linearity of the route - least deviation from the origin to destination - becomes more important for movement (Tuner, 2000; Conroy-Dalton 2003; Hillier and Iida, 2005).

The *metric length* of streets is another attribute of the urban street network. In modern cities, street length varies considerably and is constrained by both the urban fabric and planning regulations. Apart from varying across the network, overall the distribution of length in the city is skewed with a small number of very long streets and a large number of short streets. It has been argued (Hillier 2007) that this variation of long and short streets forms two distinctive geometric patterns. Urban studies of London *(ibid)* show that a long line is more likely to be connected to another long line at a straight angle, forming a continuous pattern of street connections that on a large scale outline the main skeleton of the urban grid, see **Figure 2a**. In contrast, shorter street segments tend to be more clustered and located near to long street segments, see **Figure 2b**. This agglomeration of streets tends to form a grid like a network, where short segments intersect almost at a right angle both to each other and to the longer street segments: this agglomeration of segments is built-in into the large-scale grid, see **Figure 3**. This type of street network layout geometry is encountered more often in European style of street networks, than in North American cities.

Figure 2: Two layers of street network layout: (**a**) main skeleton of urban grid, (**b**) background network

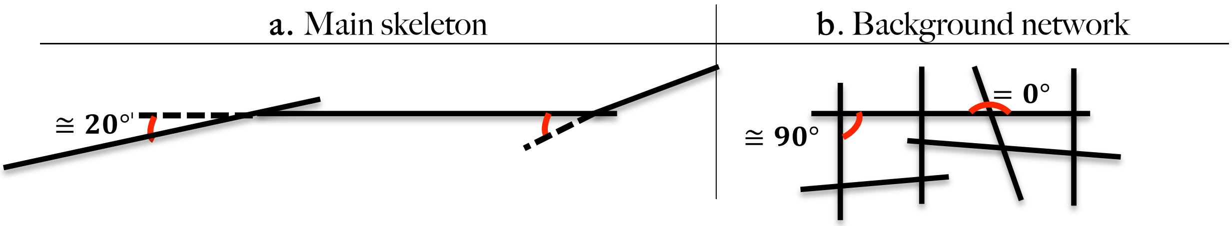


Figure 3: A part of London showing both the main skeleton of the urban network (coloured in green and yellow shades) and the background network (coloured in blue shades)

Based on street geometry, two principal layouts of the street network can be distinguished*: a grid* street network, where the dominating geometry of the street layout is orthogonal with the majority of streets intersecting at right angles, and a deformed-grid or *naturally grown* network, where the street layout has varying geometries streets intersecting at many different angles. Moreover, the orthogonal layout of the street network is commonly comprised of many longer streets than shorter ones, and the longer streets tend to be of similar length. In contrast, the naturally grown street networks have a heavily skewed distribution of street length with many short streets and few longer ones. It has been argued (Hillier, 2007) that in the context of the city, these few longer streets with large visual fields (lengths of road with uninterrupted lines of sight) are more recognisable for city dwellers than grid based networks with a similar length of street segments.

As cities gradually develop, they incorporate both layouts of the street network. Many modern cities combine the organically grown historical city centre with grid based commercial, office and housing neighbourhoods. However, overall, the grid based pattern dominates automobile-based North American cities facilitating the ease of vehicular movement that is the primary means of movement. In comparison, European cities have a predominantly naturally grown street network accommodating both pedestrian and vehicular movement. It is believed (Hillier, 2007) that the European street network with varying angles of line incidence and few longer streets, better shape the mental maps of the city dwellers than the grid based street networks dominating US cities.

In order to understand movement patterns in the city and incorporate them into the analyses that follow (Chapter 5-7) as an independent variable, the average movement flows per street segment need to be calculated. The on-site observation and quantification of movement flows for every street segment in a city are costly and unreasonable. Fortunately, the street typology categorisation can be used to infer approximate levels of street permeability, hence the approximate movement volume. However this categorisation does not always reflect real movement flows, since these categories are arbitrary assigned following administrative boundaries. An alternative solution is to quantify probabilistic movement flows based on the level of street permeability. The space syntax technique developed in the field of architecture does just that. The method converts the street network morphology into a relational graph. The technique uses network graph theory principles to analyse pairwise relations between all origins and destinations in the city. It is found (Hillier et al. 1993) that this probabilistic estimation of movement volumes per segment reflects actual movement quantities with up to 80% accuracy. In this research, this movement flow quantification is used to analyse drug crime in the city. The exact method of quantification is detailed in the next section.

4.2Street network analysis technique: Space Syntax

4.2.1. Propositions of Space Syntax

Developed in the 1970s in the Bartlett School of Architecture of University College London, *Space Syntax* is a set of mathematical techniques based on graph theory that are used to compute quantitative descriptions of the underlying structure of the street network morphology. The primary proposition of this approach is that there is a *strong relationship between movement patterns in the city and the street network* (Hillier and Hanson 1983; Hillier et al. 1993). Space Syntax research has continuously established a significant correlation between quantities of both pedestrian and vehicular movement and various graph measures (Hillier and Penn, 1996, Penn *et al.* 1998; Hillier and Iida; 2005; Turner, 2007).

Importantly, the approach treats the urban environment as a continuous whole. It suggests that the urban environment is not a set of discrete areas that are somehow joined together, but "a continuous structure in which the connecting tissue between recognisable areas is as critical as the areas themselves" (Hillier and Shabaz 2009:185). This continuous property of the urban environment is termed *configuration* (Hillier and Hanson 1983). Configuration is an abstract representation of the urban environment, where relational links are established between discrete parts of the space. Here, the urban spaces are the objects of the graph, represented as nodes, and their consecutive intersections are the edges. The underlying logic behind this is that by modelling the skeleton of the urban grid as sequences of interconnected nodes that form travel routes, the technique captures the dynamics of movement patterns occurring across the street network. Thus, the central finding of the Space Syntax method is that *configuration alone is a good predictor of movement flows.* This proposition is based on the key fact that the configuration of the urban environment is *asymmetrical*: the spatial layout not only looks, but is different when walked through different nodes in the graph. Assuming that there is an equal amount of movement passing through all spaces in the graph, some nodes will be used more for movement between the locations simply based on the fact that they have more connections and they are well positioned in the graph. Thus, these locations are considered more permeable and they attract more movement flows, in comparison to less permeable nodes.

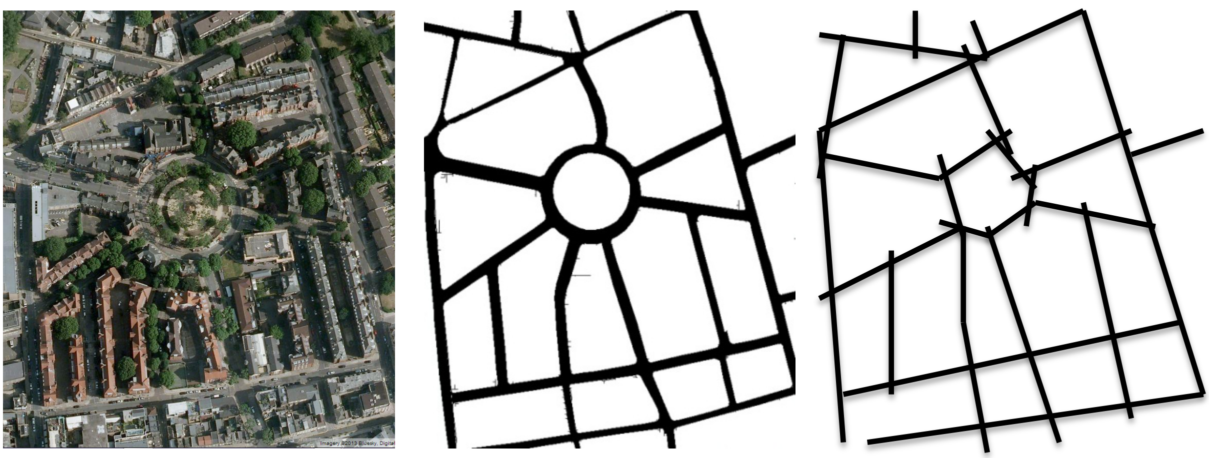
In order to systematically examine the asymmetry of the configuration, the differences between locations are measured using not a metric shortest distance, but *topological* least number of turns. This is another proposition of Space Syntax. From a behavioural perspective, pedestrians are more likely to choose routes that involve less complexity, i.e. least number of changes along the path, rather than the shortest paths (Hillier et al., 2007). In the next three sections these propositions are discussed in depth.

4.2.2. Spatial unit used in Space Syntax analysis

In order to depict and analyse the *configuraton*, the urban environment is reduced into discrete but interlinked parts. In **Figure 4b** the urban neighbourhood is cartographically represented, with a distinction made between unbuilt space (coloured in black) and built space (coloured in white). This map captures the continuous structure of the street network regardless of the type of the road (A road, local road, dead end) and its function.

Figure 4: The street network of Boundary estate in Tower Hamlets Borough represented as Google map (a), schematic map (b) and axial map (c).

a) b) c)

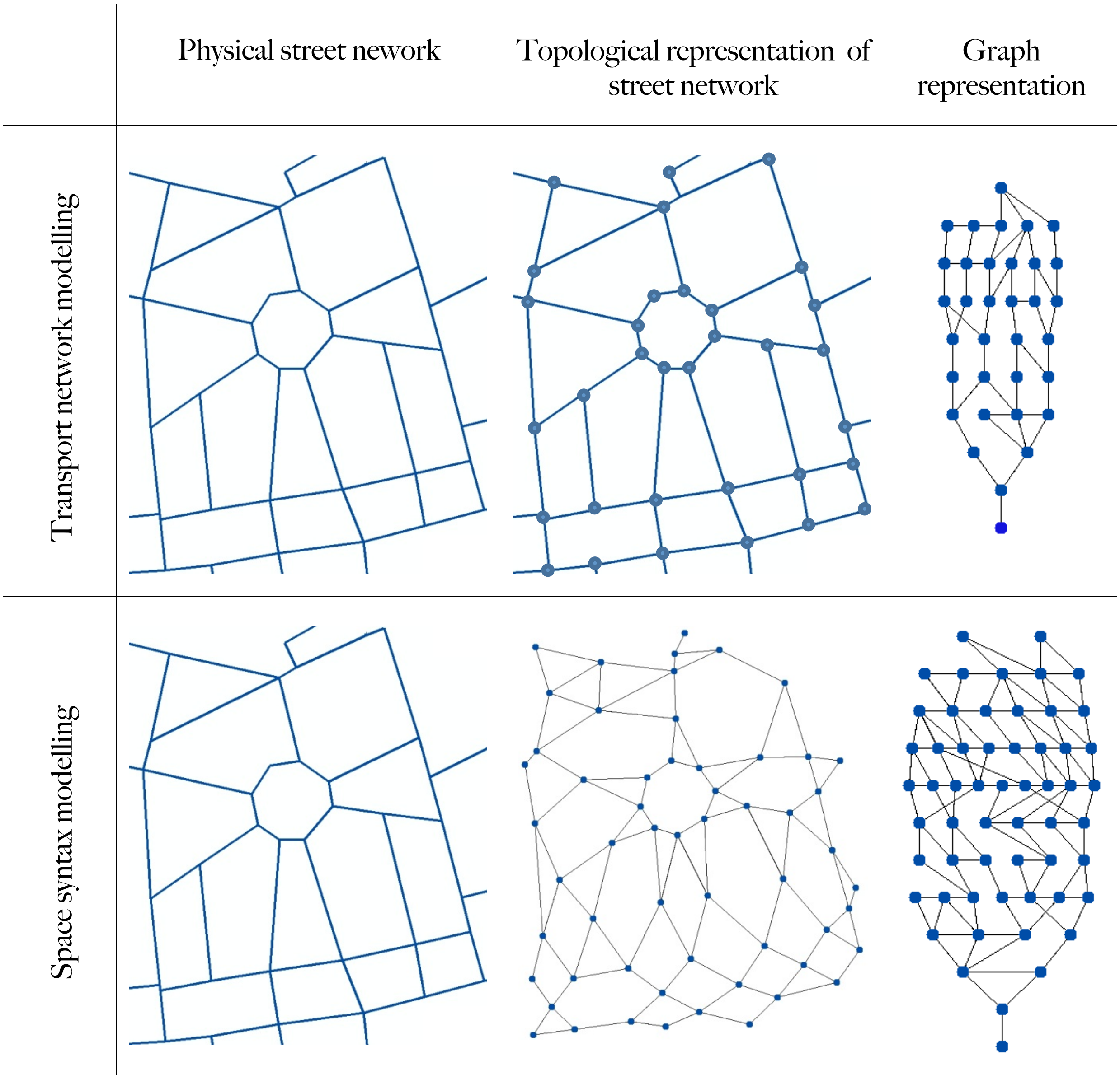


Furthermore, in order to analyse this continuous structure of urban street network, the configuration itself should be divided into meaningful *units*. The chosen unit should reflect some 'movement' aspect of the street network, so fragmenting the unit into much smaller pieces will affect its integrity. Space syntax proposes to fragment continuous urban space into the least number of lines of sight covering all available spaces representing the longest visual fields (**Figure 4c**). These lines are termed axial lines. It has been argued (Penn 2003; Hillier 2003) that in essence the axial map is a valid cognitive representation of the urban environment that people use during the course of navigation. However, the axial map has been criticised (Ratti 2004b) for not being robust enough. Since the map is manually drawn, some features of the urban layout may lead to different researchers producing different axial representations. In rebuttal paper, Hillier and Penn (2004) discuss nine key questions regarding axial line representation, addressing Ratii's criticisms. Tuner (2005) subsequently developed an algorithm to automatically and uniquely produce an axial map from a built form using Depthmap software.

Furthermore, in order to increase the effectiveness of urban network modelling, publicly available road centre-line data were used to produce syntactical maps (Turner 2007). Researchers (Turner 2007; Dhanani et al. 2012) have showed that road centre-lines could replace axial lines without losing the syntactical precision. This allows the modelling of very large areas both with great detail and without much investment of time in the production of the map. Thus, nowadays, the spatial unit of analysis could be defined as a road centre-line segment located between two junctions regardless of its length. It should be noted that although the unit of analysis is not the same across the study area, as it reflects the metric differences of streets, since space syntax concerns in the topological relationship between segments, the length of the segment becomes a less important factor.

Methodologically, there are two distinct ways of fragmenting the continuous structure of the street network into interconnected, but not overlapping discrete units. Both methods use the application of mathematical graph theory that conceptualizes any structural relationship into a set of nodes connected by lines. The first method is used to model mainly transport networks (recently re-applied to urban structures (Sevtsuk 2010) and termed transport network analysis. The second is primarily applied to the analyses of urban spatial structures and is used in space syntax analysis. The main difference between the two is that the former modelling technique converts street junctions into nodes and the streets into links (see **Figure 5**), and the latter represents the streets as nodes and the intersections as links. Thus, the nodes and links of the first model still replicate the physical space, however, in the second the primary relation is assigned to street segments, where the nodes no longer replicate real street junctions. Thus, this graph examines the interconnected pattern of lines of movement. It has been argued (Hillier and Iida 2005) that this abstract representation of the space better depicts the *lines of movement* across the network and subsequent changes in direction.

Figure 5: Topological representation of a street network structure with corresponding graph representation. a) transport network graph (34 nodes, 44 lines); b) space syntax graph (59 nodes, 116 lines)

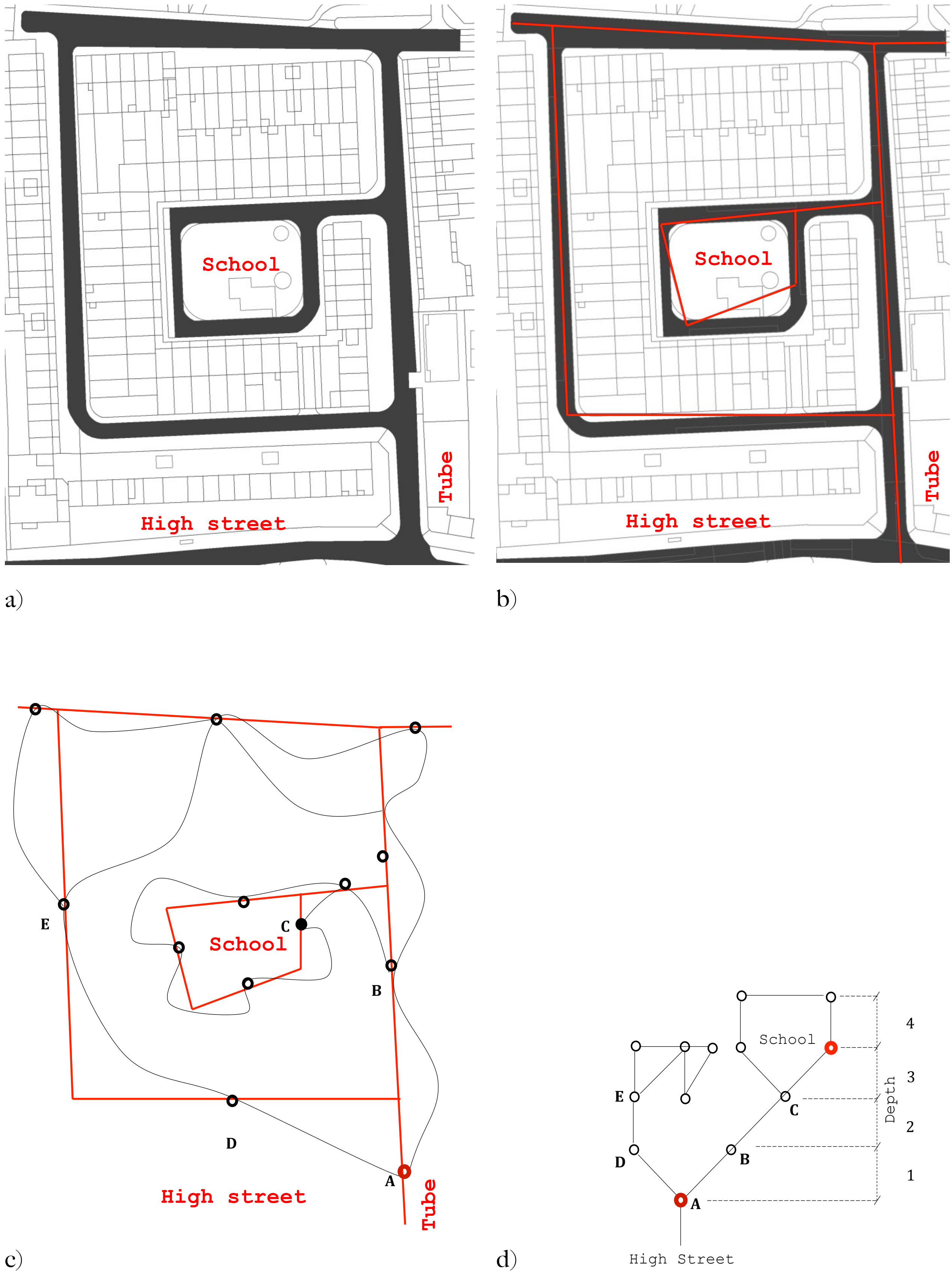


Abstracting an urban environment into a graph representation not only allows the systematic quantification of street configuration from the local neighbourhood to the city wide scale, but also captures the social aspect of the use of space at the topological level. The most intuitive notions of *control, hierarchy, asymmetry* and *depth* of spaces are traced in the graph. Consider the example in **Figure 6**, a school surrounded by housing blocks with street segments leading to the tube station and to the high street, **Figure 6a.**

The layout is reduced to line representation (**Figure 6b, c**) and converted into the graph that is arranged from the high street (**Figure 6d**). It is obvious that the street segment named 'A' controls the access to the housing block. Moreover, there is a hierarchical order in terms of accessibility: in order to reach the school from the high street, a person needs to walk through A, B and C segments, where the relationship of segment C to segment B is asymmetrical with respect to segment A. That is B is directly accessible to A, but segment C is only accessible to A via segment B. Thus, the depth of the school can be calculated as 3 segments away from the high street. On the other hand the relationship of B and D is symmetrical with respect to A – both segments are directly accessible to A. Since B and D segments are mutually symmetrical, they are located in the same level in the graph, whereas there is a hierarchical difference between A and C, thus they have a different level of depth (**Figure 6d**).

The example illustrates that the information about topological relationships between segments is sufficient enough to capture not only the navigational aspects of the space, but also to make inferences about the social structure of the given area. The deep positioning of the school, away from the high street signifies the relative privacy required for the land use to operate sufficiently. Conversely, the tube station is located on a segment with a high control value and is directly accessible from the high street for many diverse users. *Segment analysis* allows calculation of these notional measures of street network.

Figure 6: Street network represented as a configuration



4.2.3. Quantification of *movement* via measures of centrality

The primary use of *segment analysis* is to quantify the probabilistic distribution of movement quantities across the street network. Space syntax proposes that configuration alone is a primary generator of human mobility dynamics (Hillier et al. 1993; Penn et al. 1998). That is, the layout of the urban grid is organised in such a way that given a random distribution of movement flows across the street, certain street segments will benefit from a larger number of encounters making the area look busy, while other streets will have a relatively low number of encounters making the area look more private. This unequal distribution of movement quantities is based on the strategic advantageous positioning of certain street segments over other segments in the configuration. In **Figure 6**, if we assume that there is a movement flow from all segments to all others using some sense of the distance, it becomes clear that segment E potentially will have less movement flows than segment A or B. However, if segment E had direct access to the high street, the control over the housing block would be shared with segment A and in that case they would account for similar movement flows.

As mentioned earlier, every trip through the network consists of the location from which it originates, the destination where it ends and the series of accessible spaces connecting the origin to destination. Hence, space syntax considers the discrete urban spaces in the graph to function in two ways – movement *to* a space and movement *through* a space. For instance in **Figure 6** the school acts as a destination and the segments A, B and C facilitate access to the school. Furthermore, the technique adopts the geographical concept of distance decay to explain how trips are generated and distributed across the network. It is expected (statistically) that the destinations that are closer to the origin will be preferred more often than the locations further away. Following this logic, nodes that topologically have a central location in the graph will be used more as destinations than less accessible nodes. This property of the graph is assessed using a *closeness* measure of network centrality (Sabidussi 1966) referred to in the space syntax literature as *integration* (Hillier and Iida 2005). Hence, nodes that are more integrated in the urban network will be used more as a nearby destination than nodes that are less integrated or which are *segregated.* Given that all the nodes in the graph are treated as possible origins and destinations, closeness is defined as:

$$C_c(P_i) = \left(\sum_k d_{ik}\right)^{-1} \qquad (1)$$

where the integration value for the segment P_i is defined as the sum of the lengths of all shortest paths (d_{ik}) between segments P_i and P_k. In movement terms, integration captures the locations that are easy to reach from all other segments. A pedestrian will visit these locations more frequently and with less effort.

The second measure of network centrality used to assess the distribution of paths between all origins and destinations is referred as betweenness (Freeman; 1977) or syntactic *choice* (Hillier and Iida, 2005). It is defined as:

$$C_c(P_i) = \frac{\sum_j \sum_k g_{jk}(p_i)}{g_{jk}} \; (j < k) \qquad (2)$$

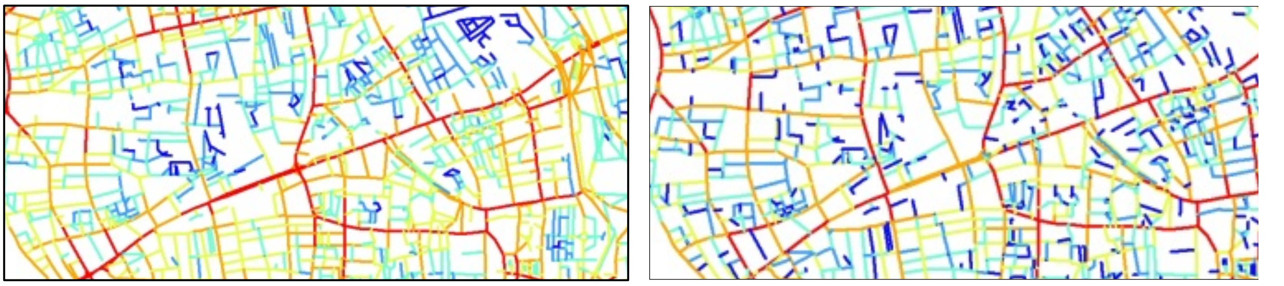
where the nodes are treated as a part of available routes, and the choice value for node *Pi* is calculated as the number of shortest routes $g_{ik}(p_i)$ passing through node P_i between origin-destination nodes p_i and p_k, divided by the number of all possible routes g_{ik} in the system between nodes p_j and p_k. In movement terms, *choice* describes how probable it is that a given segment will be used during journeys between locations. It captures the probable amount of passing by movement through each segment in the network.

The greater the separation of origin and destination in the graph, the more the betweenness measure of centrality becomes important for the network. Longer journeys will pass through a larger number of nodes than shorter journeys. However, some nodes in the graph sequence will be used for both short and long journeys, contributing to a high total betweenness value on those segments in the network.

The computer program called UCL Depthmap (Turner 2001) calculates both measures of centrality, see **Figure 7**.

Figure 7: Two measures of network centrality calculated for the same area of the street network: closeness or to-movement map (a) and betwenness or through movement map (b)

a) b)



4.2.4. Definition of the *shortest path* for segment analysis

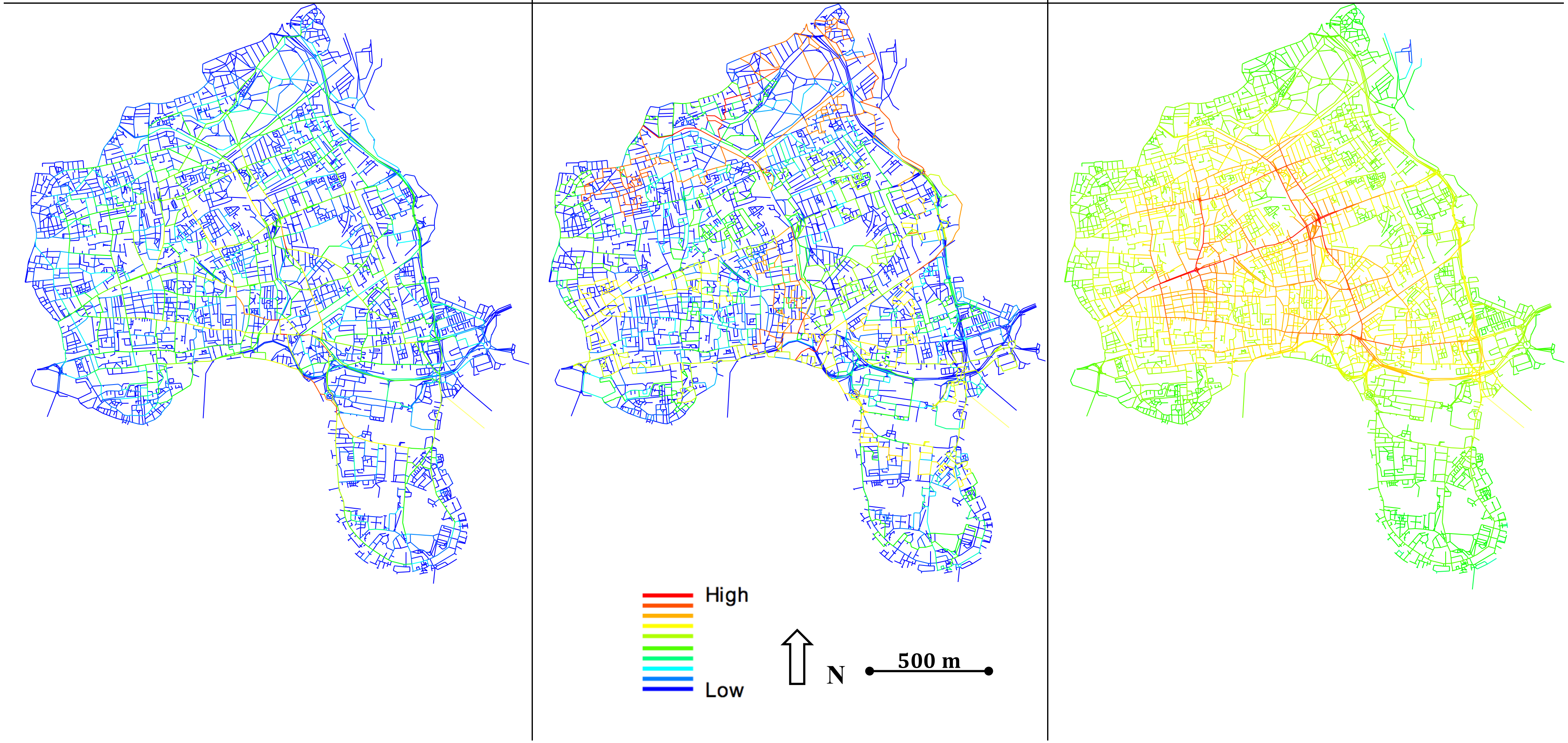
When estimating network centrality, the measure of distance, referred to as *depth* in space syntax, is used to calculate the distance between pairs of nodes. There are three definitions of distance (Hillier 2009): *metric*, *topological* and *geometric.* The metric distance for a pair of segments is calculated by measuring the physical distance between the centroids of two segments. Topological distance is defined as the fewest directional turns along the network between locations, see **Figure 8**. It is calculated by binary coding the neighbouring segments, where '1' equals to a change of direction between segments and '0' denotes that the path is straight. Finally, the geometric or angular distance is defined as the accumulated least angular change between the locations for all pairs of nodes. It is calculated by the exact angle of change in the direction between neighbouring segments.

Based on a decade of research, and field observations of aggregate movement flows across the street network, space syntax scholars have found (Hillier and Iida 2005) that during the navigation process, the *depth* or *number of turns from origin to destination* is more important to spatial perception than the metric length of the route. It is proposed (Hillier and Iida 2005) that the perceived distance is more associated with the *simplicity* of the route, rather than physical distance . Researchers argue (Penn and Dalton 1994;Tuner 2000; Dalton 2001; Conroy-Dalton R 2003; Hillier and Iida 2005) that not only does the number of turns matters during spatial navigation, but so too does the *linearity* of the selected routes. Hence, space syntax suggests that during navigation people use available visual fields to assess the topological and geometric characteristics of the street network and choose the simplest linear routes, i.e. the routes that have the least number of turns and angular deviations between origins and destinations. As Hillier and Iida (2005;pp. 553-4) observe:

> In recent years, research results have accumulated in cognitive science which suggest that the metric distance assumption is unrealistic, not perhaps because we do not seek to minimise travel distance, but because our notions of distance are compromised by the visual, geometrical and topological properties of networks.

Figure 8: Metrical, topological and geometrical distances used to calculate the shortest path between locations

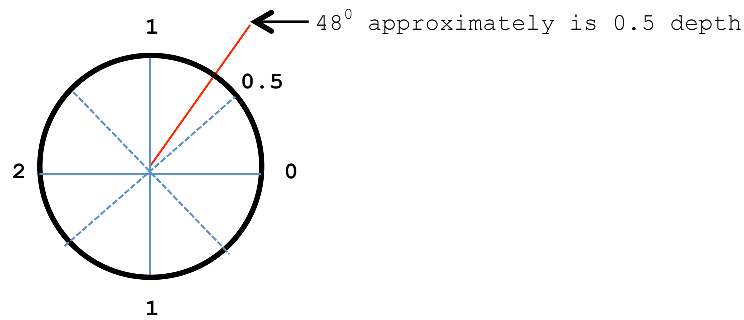
Metric distance	Topological distance	Geometrical distance



Given the assumptions about the way people navigate the urban network, currently space syntax uses the angular definition of distance to create weighted graphs. It is argued (Hillier and Vaughan 2007) that the geometrical definition of distance is the best predictor of aggregate movement across the street network. Thus, the shortest route is defined according to the accumulated least angular change between locations, where a straight connection between two lines will have a zero weight, but a 180^0 degree turn on the same line will be given a value of 2. At the intersection between two segments, a 90^0 degree change in direction equals 1. In the example of the housing block in **Figure 6**, the depth from segment A to segment B is 0 (straight line connection), but the depth from A to D is 1 (approximately 90^0 turn) and from A to E is 2 (90^0 turn followed by another turn of 90^0). So, the total depth of the path equals the sum of all segments weighted by their corresponding change of angle.

The space syntax approach (Turner 2007) adopts Montello's (1991) proposition regarding how people categorise turns along the path by rounding them to 45^0 or 90^0 degree. **Figure 9** shows the 8-bin tulip analysis that the UCL Depthmap software uses to approximate the perceived change in angle when calculating closeness and betweenness measures of centrality (the software can produce full angular analysis consisting of a 1024-bin). It should be noted that the angle of turn is always positive and the movement direction is constant, i.e. entering and exiting the segment in the same direction (Turner 2005).

Figure 9: Schematic representation of angle approximation



4.2.5. Angular Segment Analysis with metric radius and segment length weighted

Based on patterns of connections in the graph, certain nodes are more central or are more important at certain scales than others. Thus, destination preferences can be identified for local to global scales of movement. In space syntax, angularly weighted centrality measures usually are analysed at different spatial scales. The *metric radius* is used to restrict the analysis from every segment along all the neighbouring segments up to a predefined radius, indicating the number of segments being distant away from every segment treated as an origin. For example, the betweenness measure for the radius of 1,000 metres will calculate the total number of simplest linear routes for all origin-destination pairs up to the range of 1,000 metres away from every node in the graph. It has been established (Hillier and Iida 2005) that the metric radius allows identification of the street segments that are more permeable than others within the defined boundary. Additionally, the restriction by a metric radius allows avoidance of the edge effect in the graph (Turner 2001).

Commonly, two radii are used in space syntax analysis to capture the street segments that are used for *local* and *regional* movement across a case study area. There is no strict rule on defining the minimum and maximum radius, and normally the choice of radii is based on the urban characteristics of the study area: segment length, size of the urban block, whether it is an urbanised area, whether the movement is pedestrian or automobile based, walking culture and many more. Since, the research reported here used data for the Greater London area, from the previous research it is known that a radius of 800 meters equates to 10 minutes walking for local movement (see Vaughan et al. 2013) and the regional movement corresponds to 2000 metres, approximately 10 minutes of driving (see Turner 2007).

Finally, when the centrality measures are calculated using the least angular deviation distance it is recommended (Turner 2007) that segments are weighted by their length, since statistically it is expected that the longer the street, the more land uses and building entrances it will have, and hence the more movement will happen on the segment. It should be noted, that this is the case for pedestrian dominated networks rather than vehicular dominated highways.

4.2.6. Current research

In this research, Angular Segment Analysis employing metric radius and segment-weighted length is used to calculate two measures of centrality – integration and choice. In order to identify the main destinations and route preferences in the borough both measures are analysed at two scales of movement – local and regional, see **Table 1**. For the local scale of movement radii of 800 and 1200[7] metres are chosen, which corresponds to 10 -12 minutes of walking. For the regional scale a radius of 4,000 metres is selected which relates to the 20 minute drive.

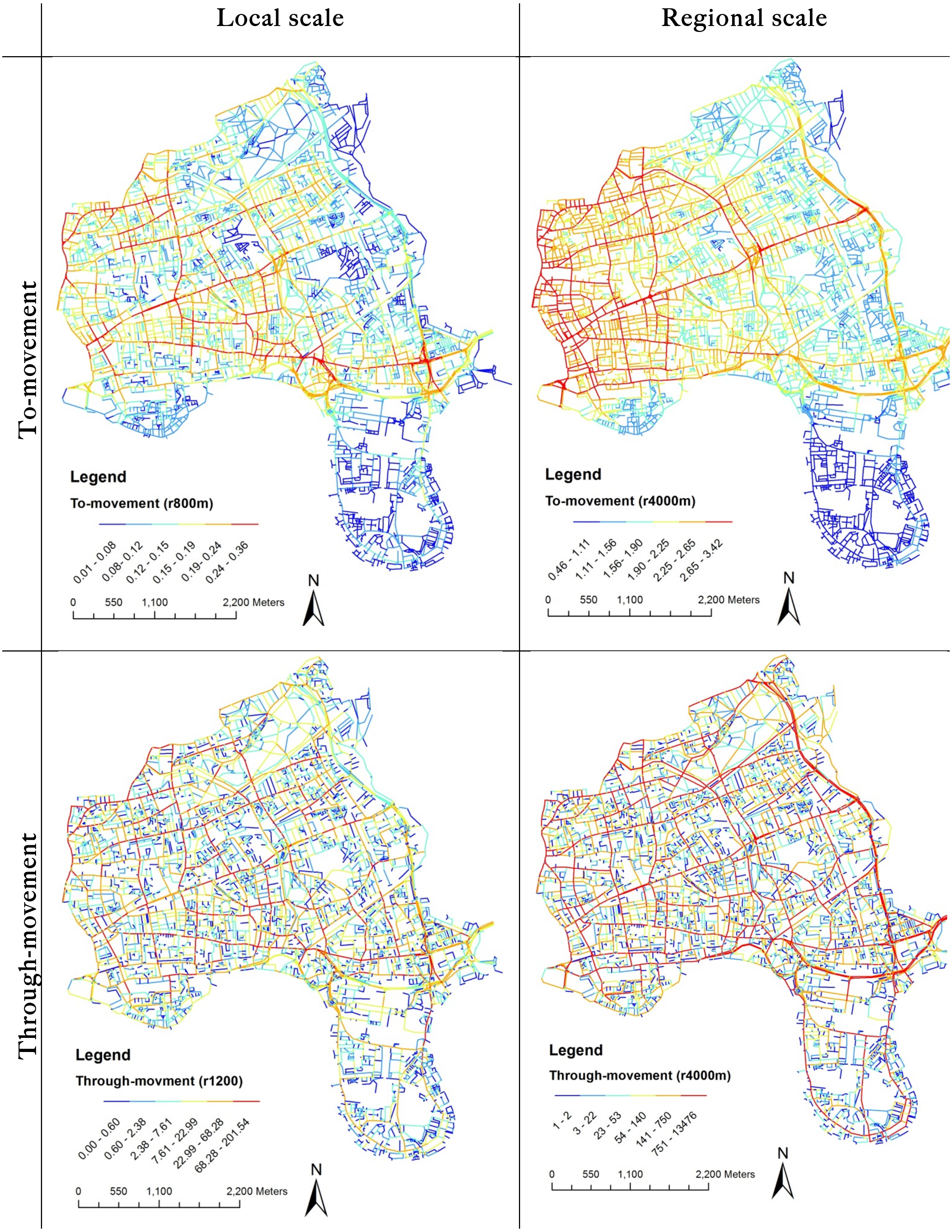
Table 1: Local and regional radii used for Angular Segment Analysis

N	Angular Segment Analysis (radius)	Purpose of the analysis
1.	Local to-movement accessibility (r800)	To identify *destination* preferences at the local scale of movement
2.	Local through-movement accessibility (r1200)	To identify *route* preferences for the local scale of movement
3.	Regional to-movement accessibility (r4000)	To identify *destination* preferences at the regional scale of movement
4.	Regional through-movement accessibility (r4000)	To identify *route* preferences for the regional scale of movement

The typical output from UCL Depthmap software is a graphical representation (*see* **Figure 10**) that shows most and least integrated routes in the system (coloured from red to blue correspondingly) combined with numerical output of each graph measure calculated for every segment. The graphical representation helps to visualise how the integration or choice values are distributed across the system and the numerical values allow statistical examination of the configuration.

[7] Recent work by the Space Syntax Limited consultancy suggests that a radius of 1200m corresponds better to local through-movement than radius of 800m (which is a legacy from axial analysis of networks for to-movement, i.e. integration).

Figure 10: Configurational permiability of the Tower Hamlets street network for two types of movement grouped according to the local and regional scale of movement, sample size n = 13,153 segments (thematic classes are derived using *natural break* distribution)



Conclusion

By computing quantitative estimates of characteristics of the street network layout based on the morphological and topological differences between locations, the Space Syntax technique allows features of urban spaces to be independent variables in statistical models. In the context of this research, the space syntax analysis enables the examination of movement dynamics at various scales in relation to drug crime, systematic analyses of drug crime patterns across many geographical locations, and the identification of common topological patterns that are not obvious in traditional geographic or hot spot methods of analysis.

In the next chapter, the spatial analysis of crime is carried out using different regression models where the *to-movement* and *through-movement* potential of the urban fabric at two scales of movement –regional and local, are used as independent variables to explore drug crime patterns in the city.

CHAPTER 5

Topological logic of drug crime: the influence of urban street network configuration on individual incidents of drug crime placement

Introduction

As discussed in Chapter 2, environmental criminology is concerned with understanding why criminals commit crime in some places and not others. Apart from socio-economic differences, scholars (Brantingham and Brantingham 1981b, 1984) suggest that the distribution of urban features and the way people navigate across the street grid influences the spatial distribution of crime. Mainly, scholars have proposed that offenders commit crimes near the 'central nodes in their lives'. These central nodes are the places where both victims and offenders live, work, and engage in shopping and recreational activities. Researchers propose (Brantingham and Brantingham 1981b) that offenders search for opportunities and commit crime close to travel routes that connect these major activity nodes. Consequently, it has been suggested that the distribution of many outdoor criminal activities will occur along main arterial routes.

This chapter looks at how the layout of the street network shapes or supports opportunities for drug crime. It considers *where* buyers and dealers position themselves to engage in transactions at the street segment level. This chapter examines the extent to which drug trading might depend on the particular configuration of the urban fabric. Mainly, the street network layout and its topological and configurational characteristics are examined in relation to drug crime.

Chapter 5 is organised as follows; first, studies are surveyed that have looked at drug crime at the micro level. Next, a list of hypotheses regarding the urban street network and drug crime placement is introduced (Part 1). Part 2 details the way the street network model of the case study area was constructed and how the drug crime incidents were aggregated to street segments. The subsequent parts examine the influence of street length in relation to drug crime both as a basic unit of statistical analysis, and as an independent variable that represents for the opportunity for drug crime (per meter length). In Part 4, all independent variables are introduced and descriptive statistics in relation to drug crime shown. Here, drug crime is examined in relation to the level of street permeability defined various ways. Part 5 of the chapter defines mathematically the non-parametric spatial regression model that was used for hypothesis testing. Part 6 explores statistically the relational links between drug supply, drug production and drug possession locations and the spatial attributes of the street network. Chapter 5 concludes with a discussion of the results.

5.1 Background

5.1.1 The drug crime distribution in the city at small scale of resolution

The spatial distribution of illicit drug dealing has been studied at many different geographical scales, from geographical areas or census units, to point or location based units. Here, only the studies that have used small spatial units of analysis are discussed. The existing approaches can be grouped into three distinct groups: location based, street blocks and street segments. The *location based* studies have looked at localised specific places that attract a large numbers of drug crimes and are represented a static points on a map. Such places identified in the literature include residential apartment blocks, where a drug house was established (Eck, 1994), or, a strategic location for drug dealing, such as a vehicular entrance from the highway into the neighbourhood (Rengert et al, 2005). The point location can represent a criminogenic facility – a bar or station that attracted drug crime (McCord and Ratcliff, 2007, Eck 1995, Rengert et al., 2005), or else, when conducting police preventive activities, an entire area, such as a park (Knutsson 1997; Groff and McCord 2012) or shopping mall (Tilley 2013) are treated as a single point location. Overall, these studies mostly aim to explain how the routine of the facilities and the lack of operational management of the given places encourage drug crime.

In comparison to location based studies, studies that use the *street block* as a unit of analysis look at the clustering of incidents of drug crime along the street block, where a street block is defined as an area that is bounded by the fewest number of streets. In contrast to point locations, this represents lower level of resolution where the spatial unit includes two elements of the urban fabric, the building and the street. Since, the size of the street block varies with the geometry of the street network layout, researchers (Rengert et al. 2005) used average street block size as a unit of analysis. The real street block dimension and the physical layouts of the block were not considered in the empirical research. This unit of analysis was used mainly to conduct on-site observation and crime prevention studies. It was found (Spelman,

1993) that those blocks that have at least one abandoned building are more probable to drug crime than those that have 24-hour security. Moreover, it was identified (Mazerolle et al. 1998) that those blocks that have place managers who work or live in the block and who are engaged with residents in crime prevention activities, will have less disorder and drug crime than those street blocks with weak place management.

Previous studies that have used the *street segment* as the unit of analysis have examined drug crime over large areas in the city. In such studies (Weisburd and Green 1995), the drug "hotspot" streets and junctions were identified based on the intelligence from the police and the physical layout of junctions and street blocks combined with drug crime reports and emergency calls. These "hotspot" streets comprised 4.4 % of the case study (Jersey City in the USA), but accounted for 46 % of drug crime. Scholars also suggested (Weisburd and Green 1995) that different drug markets were operating from one street junction to another. Others (Friedrich et al. 2009) examined the street layout of residential neighbourhoods in London in relation to drug crime. Although the street segment replicates the dimensionality of the street block, it allows incorporation of the analysis of segments that are not aligned with buildings (such as paths in the parks) and permits a comparison of neighbourhoods that have dwellings organised along the street network with those that have an estate like layout. Friedrich and colleagues (2009) found that the former had incidents of crime at the edges of the area on more permeable streets, and that for the latter incidents occurred everywhere, mostly in less permeable locations.

In their study, McCord and Ratcliffe (2007) used the length of a single street block to draw expanding buffers around specific facilities they hypothesised to be associated with drug dealing. They found that drug crime was clustered near the criminogenic facilities within a distance of one to two buffers. Researchers (Eck 1994; Rengert et al. 2005) have also proposed that the street network permeability is associated with drug crime. They have suggested that economically, advantageous locations for drug crime would provide access to locals and commuters coming to the area. Empirical research supports this idea. For instance, in San Diego cocaine-dealing locations have been found to particularly occur on street blocks that are adjacent to the arterial routes (Eck 1995). In Philadelphia researchers (Rengert et al. 2005) found that there was nearly three times more clustering of drug offences per square kilometre near highway interchanges with a decline in drug crime further away from the junction. Others (Friedrich et al. 2009) have found that after controlling for socio-economic compositions of neighbourhoods, levels of antisocial behaviour, including drug crime incidents were correlated with spatial properties of the area. In this case, drug crime was associated with the level of street permeability defined using the space syntax matrix. However, in the latter instance the authors used only simple correlations to test the relationship between drug crime and permeability without employing potentially more reliable regression models.

In summary, it should be emphasized that in the city a considerable part of people's daily routine happens along the street network and the act of crime is exception. Although the Environmental Criminology literature considers the geometry of the street network as an important element that influences the likelihood of crime (Brantingham and Brantigham 1984), drug crime has not been much analysed in consideration of movement flows and geometrical and topological attributes of the street network. Moreover, most of the drug crime studies conducted to date have been US-based, where drug dealing markets are organised mainly on the orthogonal street network, for which there is a large amount of vehicular movement. With a few exceptions (Friedrich et al, 2009) patterns of drug crime have not been examined on street networks that are non-orthogonal, such as those found in UK.

It is proposed that by systematically examining both urban characteristics and movement patterns through non-parametric statistical modelling, valuable insights can be gained about the distribution of criminal transactions along the street network.

5.1.2 Drug dealing and urban dynamics

In the context of what has been discussed hitherto, this section discusses the spatial regularities of drug crime in relation to the urban street network. It attempts to uncover the topological composition of drug dealing places in relation to both street movement patterns and street network geometry.

As discussed in Chapter 2, in order for drug crime to occur, a motivated drug dealer has to come to the same place as an attractive target – a potential drug buyer. If a guardian is absent, corrupt, or present, but not capable of preventing the crime, the drug transaction is possible. Thus, scholars propose (Brantingham and Brantigham, 1984) that crime opportunities are not randomly distributed, but have spatial regularities. These regularities reflect the spatial decision making process of the criminal (Cornish and Clarke, 1986). A part of the process involves consideration of destinations that can be visited from a given origin. It is proposed (Bernasco and Nieuwbeerta, 2005; Cornish and Clarke, 1986) that the criminal's spatial decision making involves a multistage assessment of the area, where a neighbourhood is initially selected for offending and then a specific target is selected. Thus, the criminal's journey through the network will be defined by the location where it originates, the destination it ends and the series of streets connecting the origin to destination. The distribution of these journeys across the street network will depend on a criminal's routine and degree of familiarity with the environment. Additionally, in the case of drug dealing, it has been suggested that the chosen drug site will be one that is perceived to provide high net outcome in terms of sales that is not outweighed by the associated risks of being detected (Eck 1995; Rengert et al. 2005). It is expected that from this perspective that the greatest utility locations will be closely related to the places that attract and facilitate a large amount of movement. Thus, from the set of potential destinations, the drug dealer will likely choose an area where many potential drug buyers are present or moving in/out and around the area. As has been mentioned earlier, the types of destinations that have the highest movement densities across the street network are associated with arterial or permeable routes. Thus, it is theoretically expected that the occurrence of drug crime will be more likely to take place on or near these routes. These locations are more likely to be familiar to the both drug dealer and potential buyer, they benefit from more movement passing through and they are likely to have a high concentration of diverse activities. Additionally, it is expected that the series of permeable streets leading to/from the given destinations will also have a high risk of drug crime, since they are close enough to the arterial routes, but also less risky for the dealer in terms of encountering a capable guardian(s).

As stated earlier, street movement densities are not uniformly distributed in the city: certain street segments benefit from a larger number of encounters making the area look busy and other streets will have a relatively low number of encounters contributing to a higher degree of privacy. It is expected that in comparison to drug supply locations, drug production incidents will be located on those less permeable streets, since these are the wholesale locations where drugs are produced or redistributed. Therefore, given the nature of crime they should be less associated with street mobility patterns of potential drug users, and instead be hidden away from the view of the police and others. However, in order to enable the drug production-supply chain, it is also expected that the locations of drug production will be spatially associated with drug supply locations.

Some destinations might be important for local scale of movement and others for regional or intra-city scale. There are also those that attract both scales of movement, facilitating much more movement into the area. It is hypothesised that knowledge of whether an area is permeable for local or regional visitors may also reveal the nature of the drug dealing happening in the area, i.e. whether it is a local or regional drug dealing site. It is expected that regional permeability will bring more opportunities for a regional type of drug market to be established. For instance, in the case of the current research, a considerable part of the East End of London including the recreational night-time economy, is located in the Tower Hamlets borough. Thus, this area has many visitors from other parts of London that are non-residents of the borough. So, those street segments that accommodate large-scale journeys have the potential to be associated with the regional kind of drug dealing, where potentially many more transactions will happen per unit time interval and a large variety of drugs could be sold.

Also, the length of a street has an association with its degree of permeability, since the longer the street the more immediate street connections it has. Besides, in European type of cities the long lines of movement coincide with the arterial routes of movement flows (Hillier 1999). Thus, probabilistically it is expected that per unit length more people will be encountered on longer streets than on shorter ones. Hence, it can be expected that drug dealing might be more associated with longer streets than shorter ones. However, it also should be taken into account that there will be more co-presence and potentially effective guardianship on longer streets than on shorter ones. Hence, it might be that the greatest utility locations for drug dealing are the ones that are situated in street turnings away from long lines of movement.

In summary, knowledge of movement dynamics at the street level of resolution may greatly benefit spatial understanding of illicit drug crime. In the following section, the first set of hypotheses about where drug crime is expected to occur in the city will be presented followed by the descriptive and statistical analysis.

5.1.3 Current research and predictions

In this research, it is assumed that drug dealer(s) follow a multistage decision-making process where the main goal is to maximise their utility – they seek to maximise the profit from drug sales and to avoid legal consequences. It can be added that such decision-making may not be explicitly intentional (although it might), but at some level drug dealers read spatial information and make (bounded) rational choices as to where to offend. Thus, it is expected that the choice of drug dealing sites should reflect spatial variation in the characteristics of street network, such as street types, their geometrical and topological attributes and the presence of retail facilities. **Table 1** summarises the hypothesis tested in this chapter.

The first aim of the research was to identify common locational tendencies or topological features that are associated with drug dealing. That is to examine, how much patterns of drug crime accounted for by the street network geometry and topology only. It was hypothesised that all else equal, drug supply and possession cases would tend to occur on more permeable street segments. In contrast, that drug production incidents should be associated with less permeable locations. Furthermore, it was hypothesised that drug dealing is more likely to be associated with busy streets that have a range of retail facilities. Also, activity may "spill over" from busy centres, analyses are conducted to see if the existence of a high street or active centres of mixed land uses in the near vicinity influences the spatial patterns of drug crime. In particular, it was expected that drug dealing would tend to happen on streets leading to the high street.

Lastly, the study was designed to examine the relationship between the scale of movement and drug crime in the given neighbourhood. Two movement scales were considered: *local* that is more associated with pedestrian movement within a 10 minute walk and *regional* – related to vehicular movement or a 50 minute walking distance. It was expected that the associated scale of movement would indicate the potential service area of a drug market. Moreover, it was hypothesised that the spatial distribution of drug production incidents would be different from the drug supply and possession cases, since the former is less dependent on the movement flows of potential customers.

Based on this rationale, a series of statistical regression analyses were performed, in each case, the dependent variable was the crime count per street segment and the independent variables were the degree of street permeability for movement, high street location, the segment connectivity index and the road category. Initially, several descriptive and diagnostic tests were performed in order to evaluate the data structure of both the dependent and independent variables. Dependent upon these results, appropriate regression models were chosen for hypotheses testing.

Table 1: List of hypothesis to be tested in this chapter

N	Hypothesis
	For drug supply crime
1	Drug dealing is more likely to occur on streets that have high level of permeability
2	Drug dealing is more likely to occur on streets adjacent to the high street
	For drug production crime
3	Drug production will have a different geographical pattern than drug dealing
4	Drug production is more likely to occur on streets that have a low level of permeability
5	Drug production is more likely to occur on streets that are away from high street
6	Drug production is more likely to occur on streets that lead to or are part of a cul-de-sac structure
	For drug possession crime
7	Drug possession will have a similar spatial pattern to drug dealing
8	Drug possession is more likely to occur on streets that have a high level of permeability
9	Drug possession is more likely to occur on streets that are adjacent to high streets

The influence of other spatial variables, such as the location of facilities is explored in Chapter 6.

5.2 Assembling the case study

5.2.1 Constructing the street network model

In order to examine spatial patterns of drug crime at the street segment resolution, a map was constructed that included all highways, streets, alleys and paths, hereafter the *street network*. To do this, two main data sources were obtained from the Ordnance Survey (OS). The geographically referenced Urban Path (UP) dataset was spatially joined to the Integrated Transport Network (ITN) dataset using ArcGIS10 software. **Figure 1** shows the street network for London within the M25 highway. This has a total length of 31,001 km covering an area of 1,570 km^2 (see **Table 2**). Next, a buffer of 4.5km was constructed around the Tower Hamlets administrative boundary. This was done with the intention of avoiding edge effects when computing the Space Syntax metrics. The area that contains Tower Hamlets and the corresponding buffer was extracted from the London street network. To do this, in ArcGIS the circle with 25.4km in diameter was intersected with the London street network and the corresponding line segments extracted to another file. The extracted dataset was visually inspected to ensure that all street segments were connected, especially near to the edge of the buffer. Segments that were not connected to the main network at the edge of the buffer were manually deleted.

Both original sources of street data (ITN and UP) replicate the geography of the case study area in high detail. For example, a single street located between two junctions might be comprised of multiple short lines replicating small deviations in the layout, see **Figure 2a**. The objective of this study was to examine the urban fabric from a movement perspective, where it is assumed that both drug dealers and potential buyers use their vision during the navigation process. Thus, the interest was not in the precise physical geography of the area, but the aim was to model the potential lines of vision used during the navigation process. In consideration of this, the new street network dataset was further amended. The network was edited using the simplify line cartographic tool in ArcGIS with a bend simplify option. The latter employs a shape recognition method that identifies curved lines, analyses their layout, and excludes irrelevant ones, see **Figure 2c** and **Figure 3**. **Figure 2** shows two examples. In one case, the original layout of the line was retained (Figure 2b), and in the other, it was simplified to a single line segment (Figure 2a). Additionally, very small segments (close to 0 meter) and coincident segments were eliminated from the network using the topological error option in the simplify line tool. All traffic islands were removed and multi-road intersections simplified manually. After completing all these amendments, the street network that covered both Tower Hamlets and the 4.5km buffer zone around the borough, was reduced to half its total length and the smallest segment in the network was not less than 1m, see **Figure 4** and **Table 3**. **Table 1** shows the size of the street network for Tower Hamlets borough after all amendments. The borough contains 13,153 street segments comprising a total length of 596km. It can be seen that in comparison to London, the street network in Tower Hamlets is considerably smaller and has shorter street segments.

Figure 1: London city within M25 road and Tower Hamlets borough

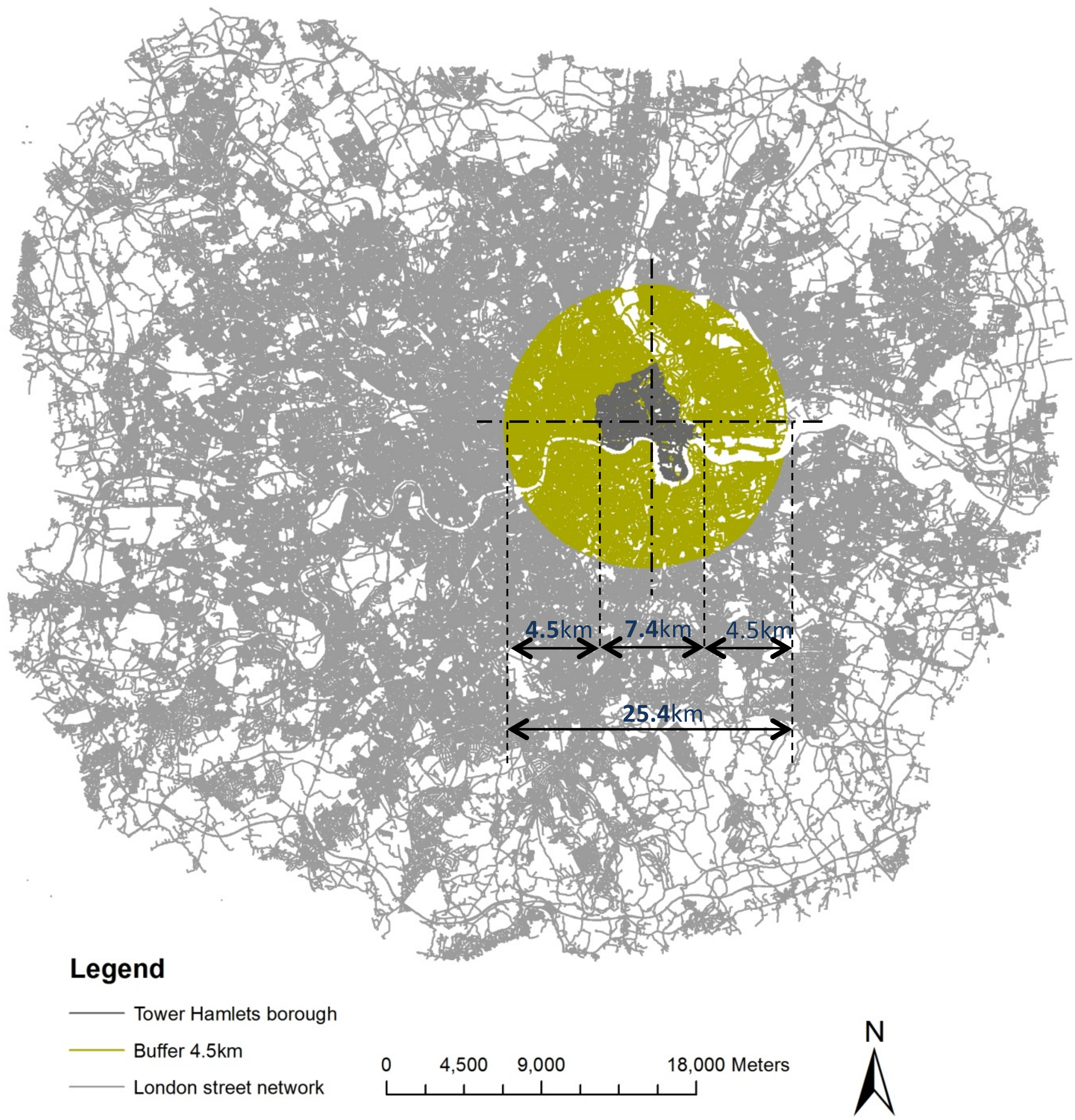
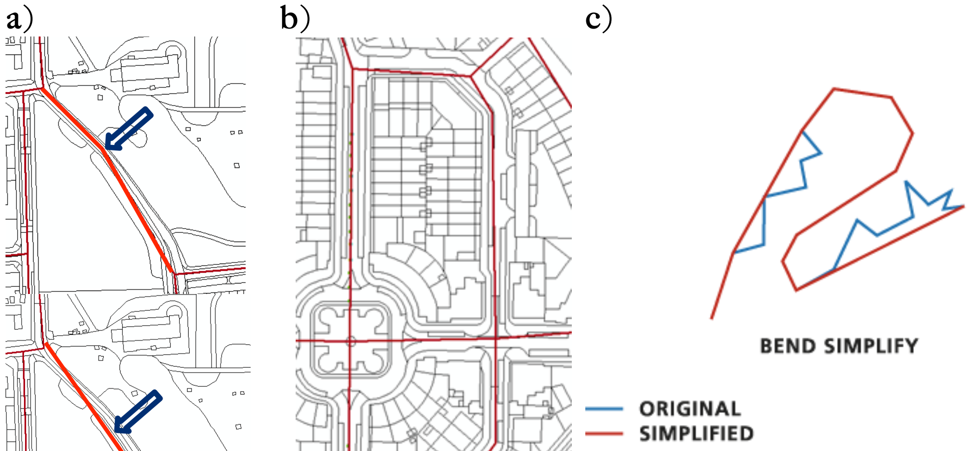


Table 2: The length of the street network for London city and Tower Hamlets borough

	Number of segments	Total length (km)	Segment max length (m)	Segment mean length (m)	Area (km^2)
London	504,441	31, 001	3,773	61.5	1,570.0
Tower Hamlets[1]	13,153	521	596	39.6	19.2

[1] statistic obtained after simplification process and covers the area within the administrative boundaries of the borough

Figure 2: Example of line cartography: (a) the network was reduced to a single line segment, (b) where it remained untouched, (c) schematic example of line cartography simplification



Source: ArcGIS Resource Centre, Copyright © 1995-2011 Esri. All rights reserved.

Figure 3: Example of a simplified street network (green) and the original network (dark blue)

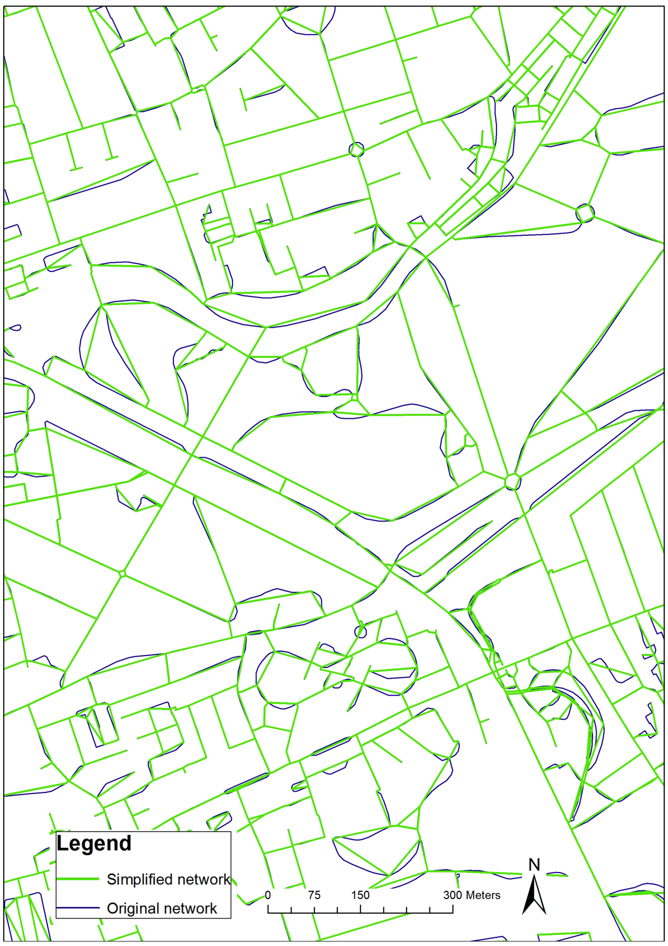


Figure 4: The simplified street network that covers Tower Hamlets borough and the 4.5km buffer

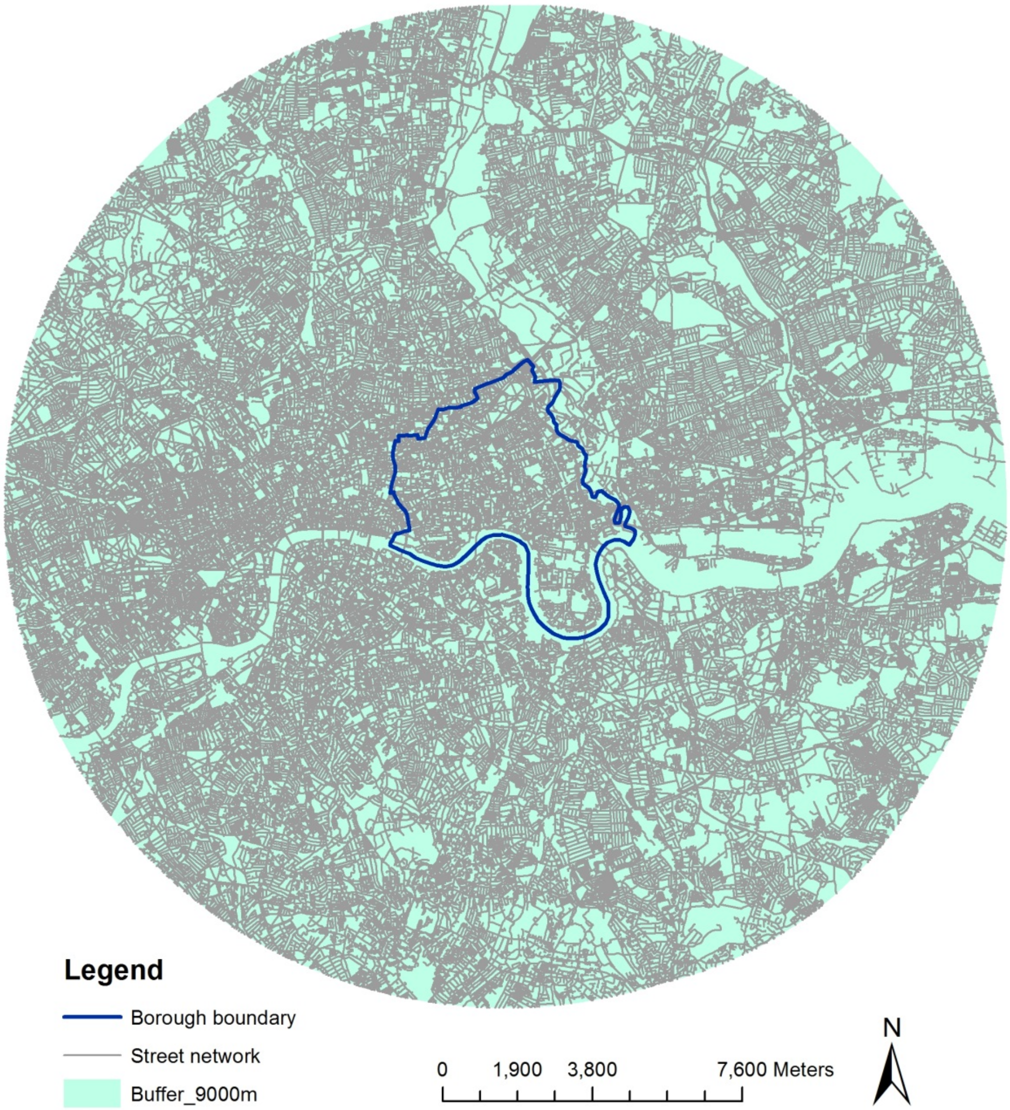


Table 3: The length of the street network that covers Tower Hamlets borough plus the 4.5km buffer before and after simplification

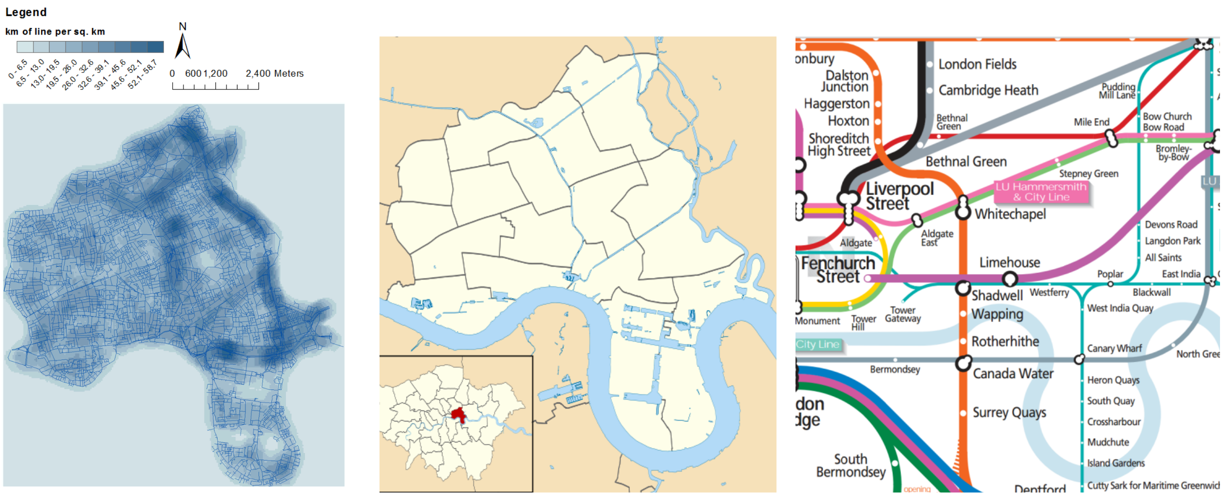
	Number of segments	Total length (km)	Mean segment length (m)	Maximum segment length (m)
Original network	180,657	8,120	50	1686
Simplified network	98,359	4,194	43	770

5.2.2 Tower Hamlet's street network geometry

The existing street network geometry of the borough is irregularly shaped with a non-uniform pattern of street connections. The segment length and the density of segments varies across the borough reflecting differences in built form between residential and busy public areas, see **Figure 5a**. The street network is also constrained by natural features and transportation infrastructure. From North to South and from South-West to East it is divided by Regent canal and Hetford Union Canal & Limehouse Cut canals, accordingly, (see **Figure 5b**). Moreover, several railway and tube lines additionally split the street network. The Great Eastern Main Line and West Anglia Line both routing from Liverpool street station on the West and splitting at Bethnal Green station, further divide the street network to the North and East, correspondingly. Also, Fenchurch Street and South End Dockland Light Railway (DLR) line split the entire south part of the borough from West to East, **Figure 5c**.

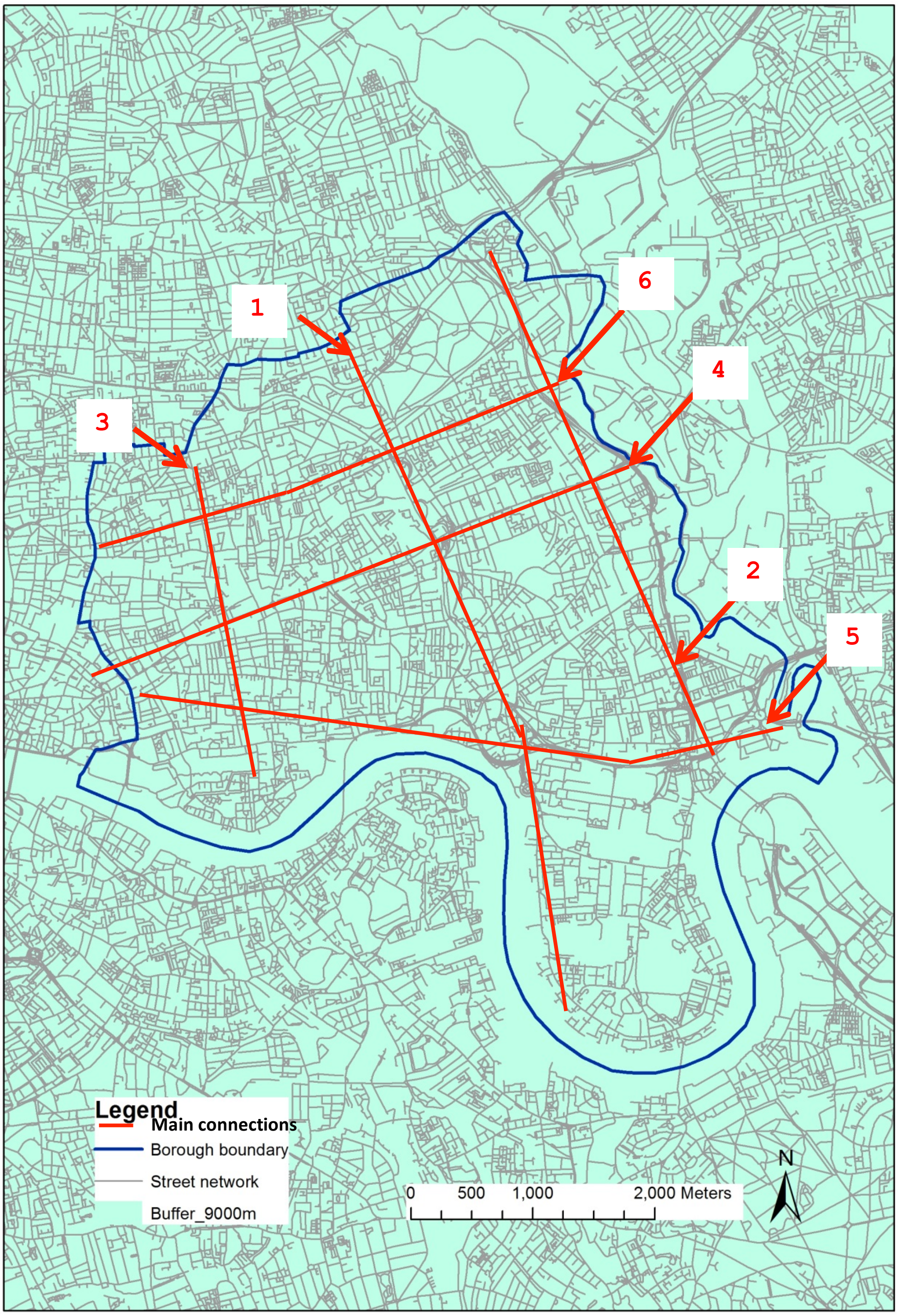
Figure 5: a) density of segments per sq. km, b) Water resources of Tower Hamlets borough, c) railway infrastructure

a) b) Source: Wikipedia c) Source © Project Mapping



Apart from these constraints, the street network has six major axes that pass through the borough and connect its parts. The East, North and South parts of the borough are connected by two links, mainly Grove Road, Burdett Road and Westferry Road group of roads (marked as '1' in **Figure 6**) and the Blackwall Tunnel North Approach ('2'). Similarly, Vallance Road with extension to Cannon Road ('3') joins the borough from North to South. The West and East parts of the borough are mainly connected by three links: Bethnal Green Road with extension to Roman Road ('6'), Whitechapel road with extension to Mile End Road ('4'), and Commercial Road with extension to East India Road ('5').

Figure 6: The major street connections of Tower Hamlets borough marked in red



5.2.3 Aggregating crime incidents to street segments

In order to analyse pattern of crime at the street segment level, a crime incident based street segment model was created. The 6,605 geocoded crime points were aggregated to the 13,153 segment lines using the spatial join tool in ArcGIS (see **Table 4**). However, prior to implementing the spatial join function, the crime points were inspected. The majority were not aligned with the street network. This was due to the fact that in practice, the police assign the crime incidents to building postcodes, thus in the majority of cases the geocoded location of the crime coincides with the centre of the building or a plot and may be offset from a road by some distance. In consideration of this, the nearest distance from crime points to segment lines was calculated using the proximity tool in ArcGIS. **Figure 7** shows that about 75% of the offences for the three drug crime types appear to be within 20m of a road. The rest were more than 20m away and were located in parks or large industrial land plots.

Table 4: Summary statistics of the spatial units used to create the crime incident based segment model

Spatial unit name	Count	Spatial unit type
Street segment	**13,153**	*Line*
Crime data	**6,605**	*Point*
– Production	93	
– Supply	732	
– Possession	5,780	

The crime points that were less than or equal to 20 meters away from a road were automatically assigned to the nearest segments using the snap tool in ArcGIS. The accuracy of the snapped points were double checked visually against the basemap with building footprints and corresponding postcode boundaries. In most cases, the postcode polygons for the crime events largely followed the street network (**Figure 8a**), there were cases when the crime incidents were located at the building corner near a street junction (**Figure 8b**). For these cases, the points were manualy assigned to the segment on which the building entrance was located. All crime points that were more than 20 meters away from a road were manually assigned to the nearest segment, see **Figure 8c**.

Figure 7: Boxplot to describe nearest distance from each crime point to street segments for the three drug types

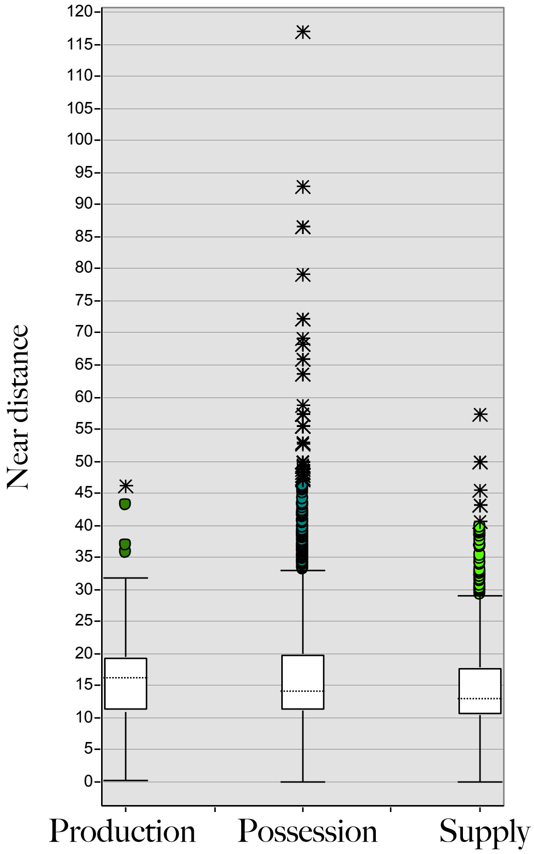
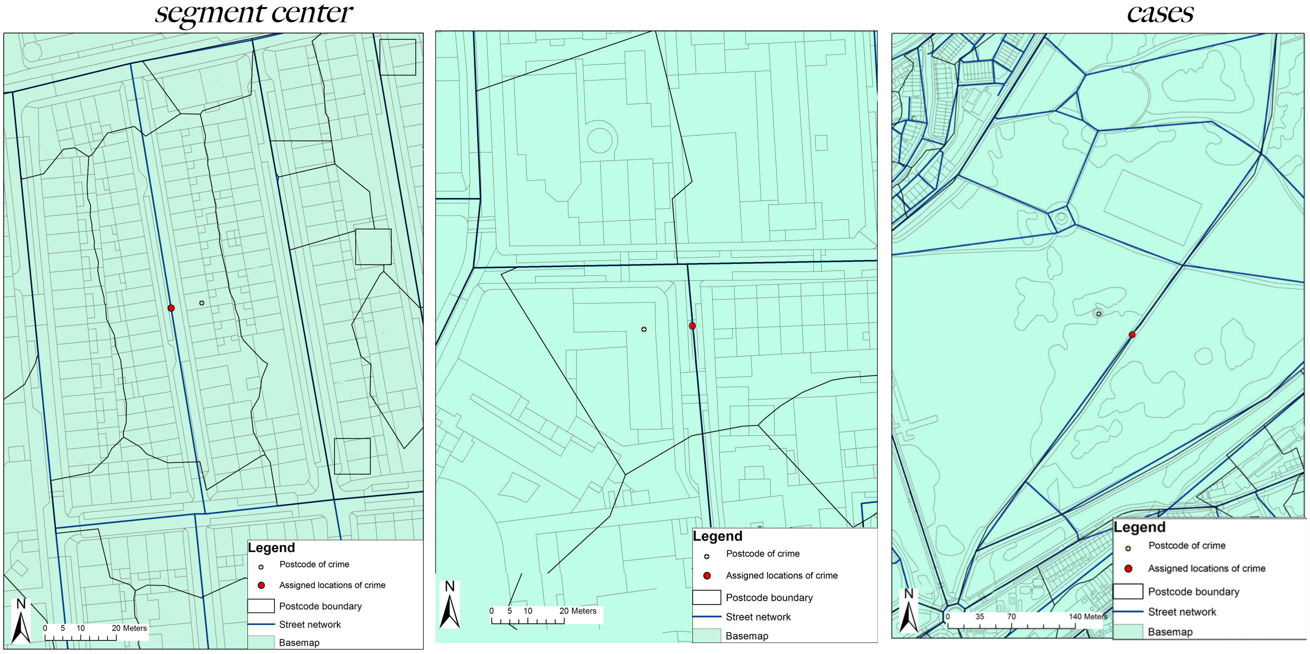


Figure 8: Examples of crime point location (red) in relation to building postcodes (yellow) after assigning the incident to a segment

a) cases located in the segment center *b) street junction cases* c) *park and industrial outlet cases*



5.3 Descriptive analysis

5. 3.1 Network geometry and drug crime

Although a number of many studies looked at drug crime at a small scale of resolution, in most cases they do not explicitly consider the street network layout. Moreover, in previous studies by simply dividing the case study area into fixed length and non-overlapping spatial units, the street network geometry and pattern of street connections that permits or restricts movement, was excluded from the analysis. In this research, the geometry of the street layout is explicitly examined.

Length is a basic geometrical property of a street and the street network as a whole. The street network of the urban environment is comprised of numerous segments of different length connected to each other. The length measures the distance or how far apart are two discrete locations that are connected with one or more street segments. In this research, the crime point incidents were aggregated to the non-overlapping segments of varying length. This spatial unit is not constant and reflects the physical length differences across the street network. In a sense, the length of the segment describes the dimensionality of the spatial unit of analysis. Thus, in theory the aggregation of crime points to street segments leads to a spatial unit size problem (Openshaw 1984) where longer segments have a higher likelihood of having many more crimes in comparison to the shorter segments. This implies that the length of a street will have a statistical influence on the number and distribution of crime counts.

In order to control for this problem, segment length was included in the regression analysis as a separate independent variable. Thus, the statistical model determined how much variation in drug crime counts was accounted by segment length as well as other factors.

Figure 9 suggests that in the case study area, there are more short street segments than longer ones. Thus, the street network replicates the European type or non-planned street network structure. The shortest segment length in the network was 1m and the longest 542m.

Figure 9: The street network coloured according to length using natural break classification

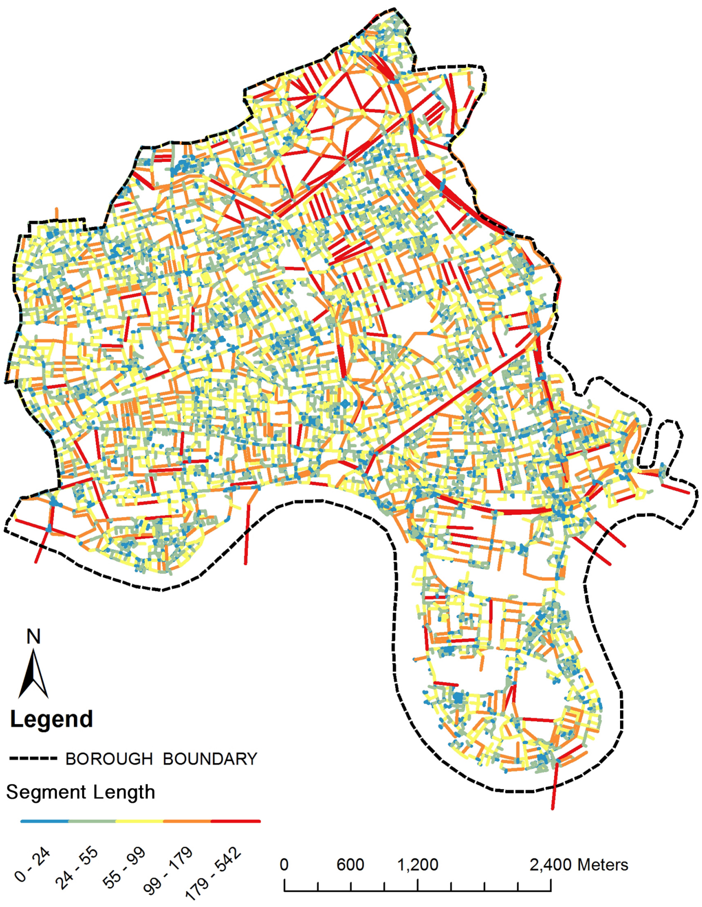
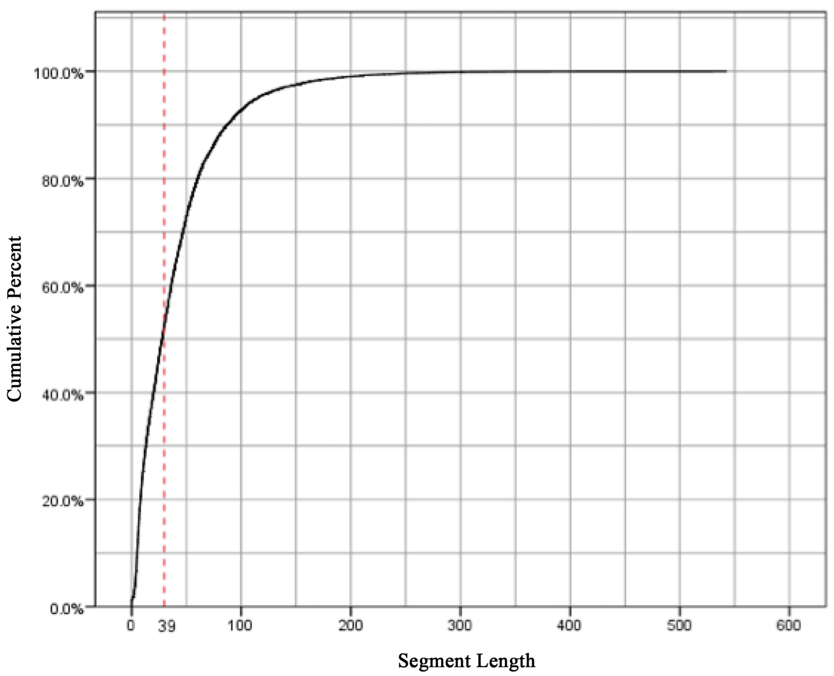


Figure 10: Cumulative frequency distribution of segment length in meters (n= 13,153 segments)



The Empirical Cumulative Distribution Function (ECDF) shown in **Figure 10** indicates that segments up to 39 meters long comprise 50% of all segments. Figure **10** also indicates that 93% of street segments are less than 100 meters. **Figure 9** illustrates how street segment length varies across the street network with the longest segments located mainly in the parks. However, the length of the segments should be interpreted with caution since the large volume of street segments with small length is also due to the cartographic technique employed and the way the map was produced. In the subsequent section, analysis will be conducted to examine the extent to which the length of the street segments influences the statistical distribution of crime counts.

5.3.2 Street segment length and drug crime

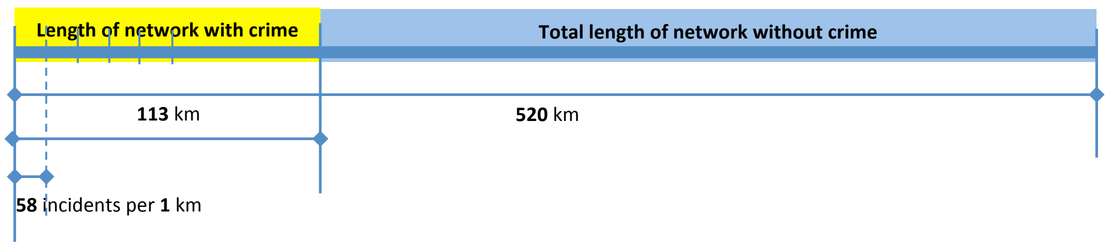
The *density* of crime per segment kilometre of street network was calculated for every category of drug crime. If L_c is the total length of crime prone street network, and C_i is the count of crime incidents for drug crime type i, then the density of drug crime per kilometre of crime prone street network is defined as:

$$\mathrm{D}_c = \frac{C_i}{L_c} \qquad (1)$$

Table 5 shows the number of drug crime incidents in relation to street network length. It can be seen that 113km of street network (one fifth of the total street network) is crime prone. On average, there were 58 incidents of drug crime per kilometre of network or 4 incidents of crime per street segment over the 2-year period considered. Drug crime tends to happen on longer street segments (75m) than the mean segment length for the entire network of 39m (see Figure 10). The same trend can be observed when drug crime is disaggregated according to crime type. Here, the highest density per kilometre of crime prone street network was for drug possession cases (55 incidents) followed by drug supply cases (25 incidents). Here also the crime prone segments are longer than the average length of streets across the entire network.

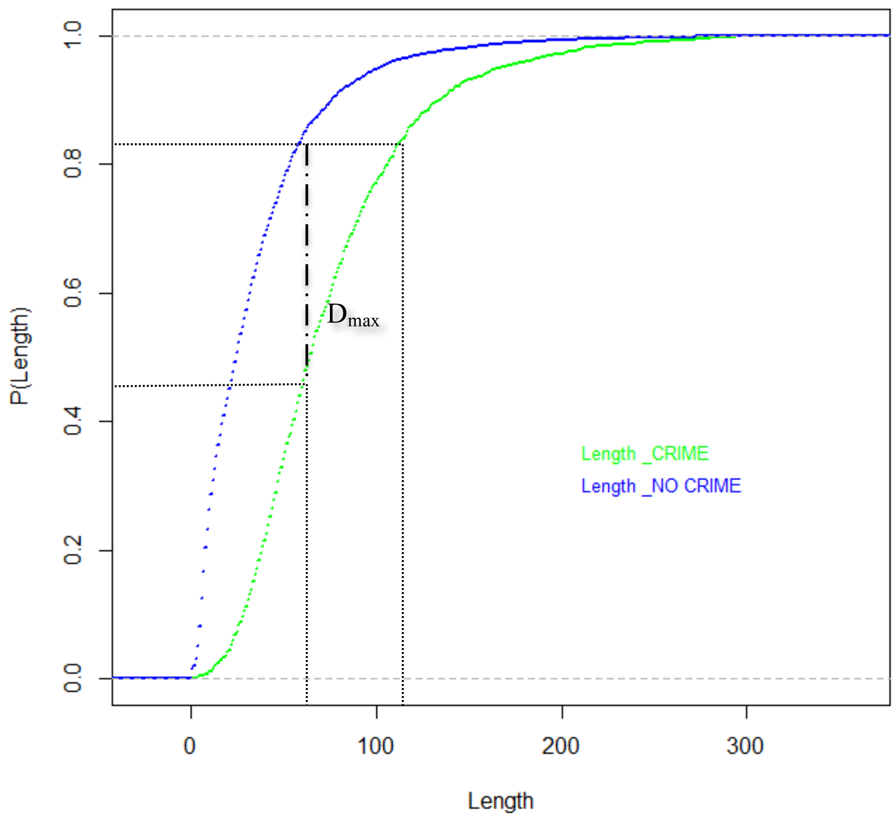
Table 5: Density of drug crime incidents per street network unit length

Crime Type (Number of incidents)	Street network **total length**	The **total length** of **crime prone** segments, km	**Maximum** crime prone segment length	**Mean** crime prone segment length	**Median** crime prone segment length	**Density** of crime count per network km	**Average count** of crime per segment
ALL CRIME (N =6,605 incidents)	521km (N = 13,153 segments)	113km (N=1502segment)	334	75	64	~ ***58*** *incidents per km of street network*	~ **4** *incidents per segment*
SUPPLY (N =732 incidents)	521 km (N = 13,153 segments)	30 km (N=363 segment)	307	82	73	~ ***25*** *incidents per km of street network*	**2** *incidents per segment*
PRODUCTION (N =93 incidents)	521km (N = 13,153 segments)	8 km (N=85 segment)	287	90	77	~ ***12*** *incidents per km of street network*	**1** *incidents per segment*
POSSESSION (N =5,780 incidents)	521km (N = 13,153 segments)	104 km (N=1,384 segment)	334	75	64	~ ***55*** *incidents per km of street network*	~ **4** *incidents per segment*



To examine these differences more systematically the crime prone street segments were compared to those that were free of drug crime. Here, the street network data were divided into two samples: street segments on which drug offences occurred and those on which it did not. The empirical cumulative distribution function (ECDF) for both samples were then calculated to see how similar are the two distributions were in terms of segment length. **Figure 11** shows the two ECDF distributions for street segments with and without crime. It can be seen that 82% of street segments without crime are up to 80 meters long, but the majority of crime prone segments (82%) are up to 120 meters. A two-sample Kolmogorov-Smirnov test (D = 0.468, p-value < .001) indicated that the two samples of street network length were statistically different. Thus, it is plausible that the longer street segments are targeted more for drug dealing than the shorter ones due to more opportunities present per street kilometre. However, it also should be taken into account that in the street network configuration, linear (and hence longer) routes tend to have more potential for movement than shorter segments; that is, they are likely to carry more offender and target traffic to start with.

Figure 11: ECDF of street segment lengths with and without crime, sample size n = 13,153 segments



The crime data were further disaggregated according to ranges of street segment length. **Table 6** illustrates the crime densities per kilometre of street network according to seven ranges of segment length with an increment of 50 meters. Here, for every range of segment length the crime density was calculated according to **equ.1** (note: both segments with and without crime were included). This simple approach allowed an examination of the variations in crime densities across different ranges of segment length.

It can be seen that out of 13,153 segments the majority (37%) are less than 50 meter long, followed by segments of up to 50-100meters long (35%), see **Table 6**. The remaining segments (28%) were more than 150 meters long. So, there are more short street segments than long ones. For the drug supply cases it can be seen that although only 15% of the street segments are 150 meters long, they have the highest density of crime per street network kilometre (~295). For drug production and possession cases the highest density of crime per kilometre have the segments ranging between 50 to 100 meters in length and comprising 35% of the network correspondingly.

To see if differences in line density were reliable, the standard error of these crime densities was calculated per street range category and plotted as an error bar, see **Figure 12**. This is a good estimator of the uncertainty in a value, since it shows the calculated error in the measurement. Thus, the wider the range of error bars, the less confident or stable is the value. The standard error is estimated by dividing the standard deviation (s) by the square root of the sample size (Fields 2005:p15):

$$\widehat{\sigma_M} = \frac{s}{\sqrt{n}} \qquad (2)$$

Figure 12 shows that the crime densities change non-linearly from range to range, suggesting that the effect is more than just statistical chance.

Having established that patterns so far observed cannot be explained by differences in opportunity alone, in the next section, the second independent variable, which is the street movement permeability, is examined.

Table 6: Density of drug crime incidents per street network unit length according to variation in length

DRUG SUPPLY CASES

N	Segment **length range**	**Frequency** of all segments	**Total length** (Km)	**Fraction** from total street network (%)	**Count** of incidents	**Density** per street network km
1.	0<length <50	9542	194.2	37.2	188	96.8
2.	50<length <100	2625	180.5	34.6	272	150.7
3.	100<length <150	639	76	14.5	224	**294.7**
4.	150<length <200	209	35.5	6.8	18	50.7
5.	200<length <250	86	19	3.6	22	115.7
6.	250<length <350	44	12.5	2.4	8	64.0
7.	350<length <550	8	3.3	0.6	0	0.0
	Total	13,153	521	100.0	732	

DRUG PRODUCTION CASES

N	Segment **length range**	**Frequency** of all segments	**Total length** (Km)	**Fraction** from total street network (%)	**Count** of incidents	**Density** per street network km
1.	0<length <50	9542	194.2	37.2	19	9.8
2.	50<length <100	2625	180.5	34.6	47	**26.0**
3.	100<length <150	639	76	14.5	18	23.7
4.	150<length <200	209	35.5	6.8	3	8.4
5.	200<length <250	86	19	3.6	3	15.8
6.	250<length <350	44	12.5	2.4	3	24.0
7.	550<length <550	8	3.3	0.6	0	0.0
	Total	13,153	521	100.0	93	

DRUG POSSESSION CASES

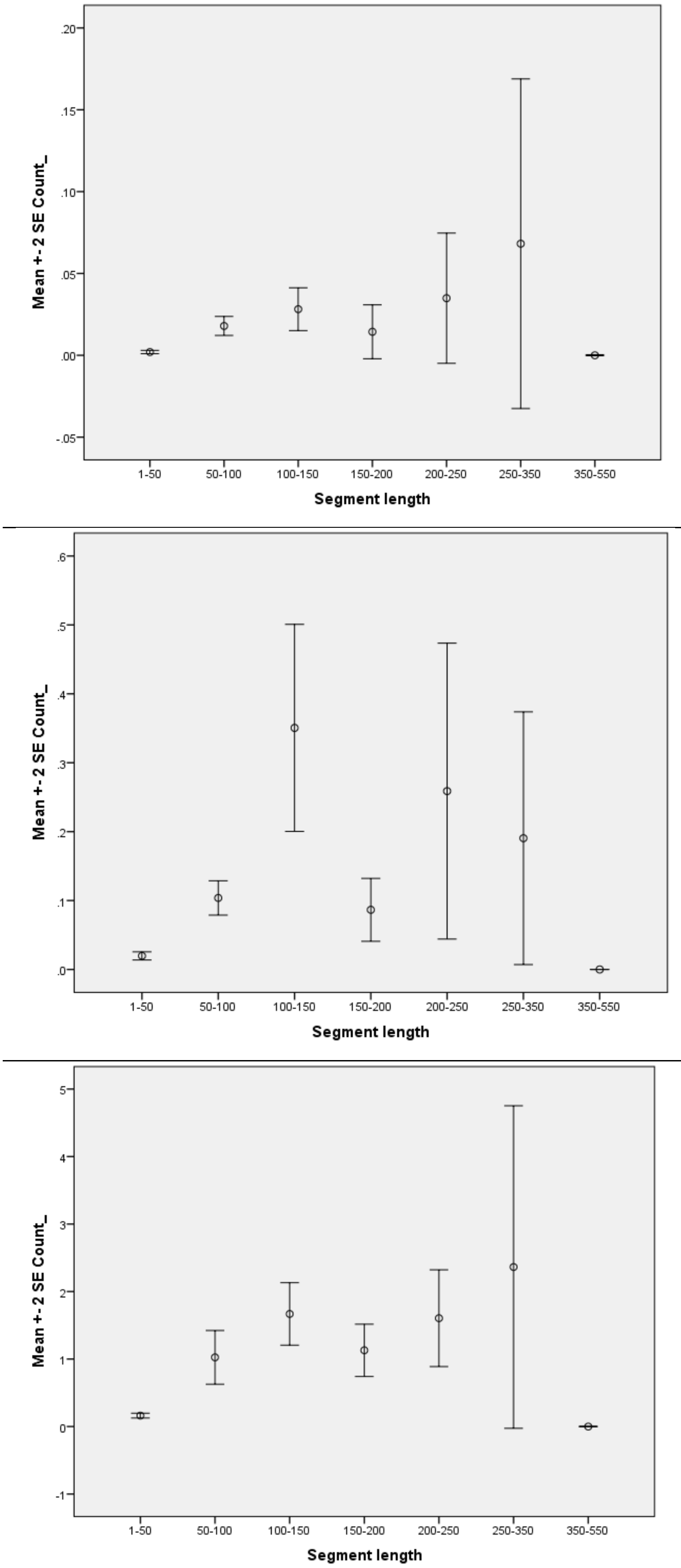
N	Segment **length range**	**Frequency** of all segments	**Total length** (Km)	**Fraction** from total street network (%)	**Count** of incidents	**Density** per street network km
1.	0<length<50	9542	194.2	37.2	1545	795.5
2.	50<length <100	2625	180.5	34.6	2691	**1490.8**
3.	100<length <150	639	76	14.5	1066	1402.6
4.	150<length <200	209	35.5	6.8	238	670.0
5.	200<length <250	86	19	3.6	136	715.8
6.	250<length <350	44	12.5	2.4	104	832.0
7.	350<length <550	8	3.3	0.6	0	0.0
	Total	13,153	521	100.0	5780	

Figure 12: Standard error bar with $\pm\ 2\ SE$ representing the crime densities per kilometre of street network, grouped according to segment length and drug crime type

Drug production

Drug supply

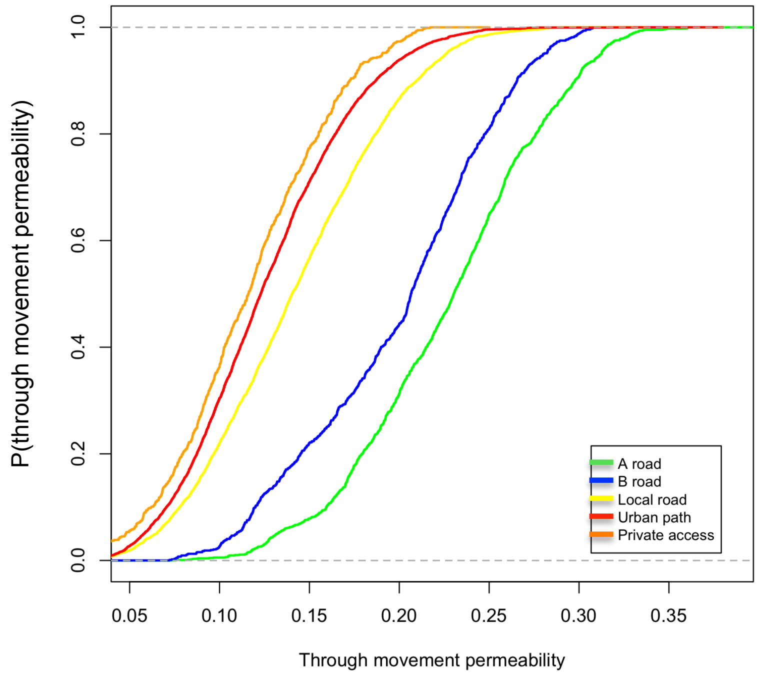
Drug possession



5.3.3 Permeability and drug crime

The aim of this chapter is to identify common locational tendencies that might explain topological regularities assosiated with drug dealing locations in the urban environment. In particular, the analyses will explore the extent to which patterns of drug crime are accounted for by variations in the degree of permeability across the street network layout. Here, the dependent variable is the count of drug crime aggregated to street segments and the independent or predictive variable is the level of street permeability. This can be measured in at least three ways: *administratively* according to street categories, *topologically* according to street connectivity and *configurationally* according to through-movement and to-movement potentials. All definitions refer to the notion of movement; that is, how relatively permeable the given street segment is for movement. However, they measure the degree of permeability in different ways. In the case of road categories, permeability is defined by planning regulations and sometimes can be somewhat artificial. For instance, A roads usually carry a large volume of movement and are referred to as permeable streets; however, some B roads can also be well used and operate like A roads. Thus, although there is a change in the category of permeability, in reality both roads might accommodate similar volumes of movement. **Figure 13** shows that each type of road defined administratively varies considerably in terms of its configurational level of permeability, however, A and B type of roads have more similar permeability levels in comparison to local roads and urban paths.

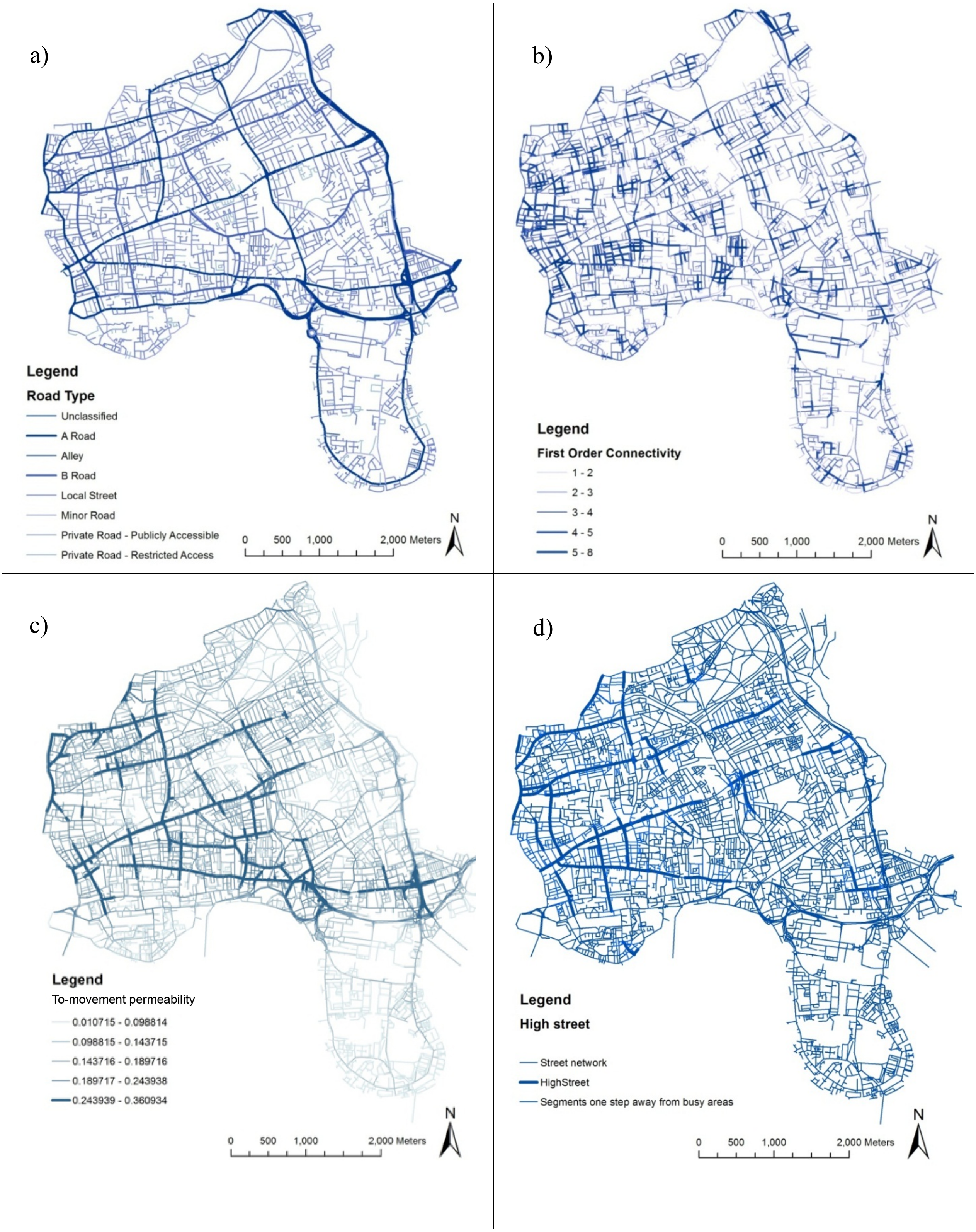
Figure 13: ECDF of through movement permeability defined using space syntax matrix and grouped according to different categories of roads defined administratively



As discussed in the introduction, physical permeability is defined from the pattern of street connections and with the strategic positioning of a given street segment in the network. So, a more refined categorisation and identification of permeability should be employed. Urban studies research of cities quantify the probabilistic distribution of movement and corresponding level of permeability by adopting a graph theory approach, mainly the concept of mathematical betweenness and closeness (Freeman 1979). The *space syntax* technique (Hillier and Hanson 1983) uses a street connectivity graph for which street segments are represented as nodes in the graph and street intersections as topological links that connect those nodes. The status of every segment (i.e. node) in the graph is calculated according to pre-defined metrics. A more detailed account of the technique was given in Chapter 4, however, here it is worth recapitulating that the space syntax metrics estimates permeability in two ways. Space syntax uses the concept of *depth* or topological distance to measure the distance between pairs of nodes. The nodes that are more central in the graph or have the least depth are considered to have high values of closeness or *to-movement* permeability, and nodes that have high values of betweenness or *through-movement* permeability are considered to be heavily used for journeys between pairs of nodes. Both measures of movement potential identify those street segments that are on average more permeable than the rest of the network. Each of the measures has been found to accountaccount for up to 75% of movement volumes in a recent study (Hillier and Iida 2005).

Additionally, it has been argued (Hillier et al. 1993) that when retail land uses are considered with highly permeable segments, volumes of movement are multiplied. Thus, more movement is expected along a given segment. In relation to this point, it was hypothesised (Chapter 5 and Chapter 6) that drug dealing is likely to be associated with busy streets that have a number of retail facilities. In order to capture all such streets, a database on the location of 'high street' was used so that these could act as a proxy for relatively busy commercial streets. In what follows, the role of the high street in the distribution of crime is examined. It should be noted that this kind of street with similar configurations of shops exists in many European countries, though it might be given a different name. **Figure 14** shows the case study area coloured according to four different classifications of street permeability. In the next sections, each of these definitions of permeability will be examined individually in relation to drug crime.

Figure 14: Street network coded according to road category (a) connectivity index (b; counts according to *natural break* distribution), configurational permeability (c; values according to *natural break* distribution) and high street (d)



5.3.3.1 Road Category and Drug Crime

The categorisation of road type adopted was from the Integrated Transport Network (ITN) layer produced by the Ordnance Survey (OS) as a complete national road network for Great Britain. It has nine main categories of road types (see Table 7), classified as 'A' and 'B' road, local and minor road, and private road with public or restricted access. A public road is classified as an 'A' road if it connects areas of regional importance. A public road is classified as a 'B' road if it connects the places of local significance. Minor roads connect B roads together. A public road is classified as a local road if it provides access to houses or land, generally not intended for through traffic. A private road with public access is a road within a property boundary where access to the public is considered usual for at least some part of the day. A private road with restricted access is a road within a property boundary where access to the public is restricted by physical or administrative means or is not considered usual. According to this classification, A roads are considered to be the most permeable, since they connect large scale movement, while private roads are associated with a small level of movement permeability.

Table 7: Categories of road types with corresponding length statistics for the Tower Hamlets area

Road type	**Total length** (Km)	**Fraction** from the whole network (%)	**Maximum** segment length (m)	**Mean** segment length (m)
A road	38.7	7.3	542	47
Primary road	27.5	5.2	596	54
B road	22.5	4.2	334	50
Minor road	28.0	5.3	306	51
Local road	226.0	42.8	323	50
Private road	36.3	6.8	337	44
Road link, roundabout	18.0	3.4	331	30
Alley	1.8	0.3	203	63
Urban pathways	130.0	24.6	407	25
Total Network	**527.0**	100.0		

The street network of the case study area is mostly comprised of local roads (42%) and urban alleys and pathways (25%), see **Figure 15** and **Table 7**. It can be seen that local roads are evenly distributed across the study area, implicitly highlighting the great number of residential neighbourhoods. Urban pathways are situated mainly along the water canals crossing the borough from North to South and from South-West to East. They also indicate the locations of parks and squares in the borough. Some of the paths are the longest street segments in the network (up to 407m). Given that geographically the borough is situated in the zone 2 of the London transport system (that consists of 6 zones), and is not far from central London, it has 'A' type of regional connection roads passing through the borough connecting east London to the city centre and to the South of London. In comparison to the rest of the network, the A roads are quite long and highlight the linear structure of the street network.

The cumulative distribution of streets according to road categories (see **Figure 16**) shows that a considerable proportion of the network of roads is comprised of local streets and urban paths. Overall, the majority of the former category is 100-150m in length and the latter of 100 m long, but there is also small proportion of very long such segments.

Figure 15: Categories of road types for the Tower Hamlets area

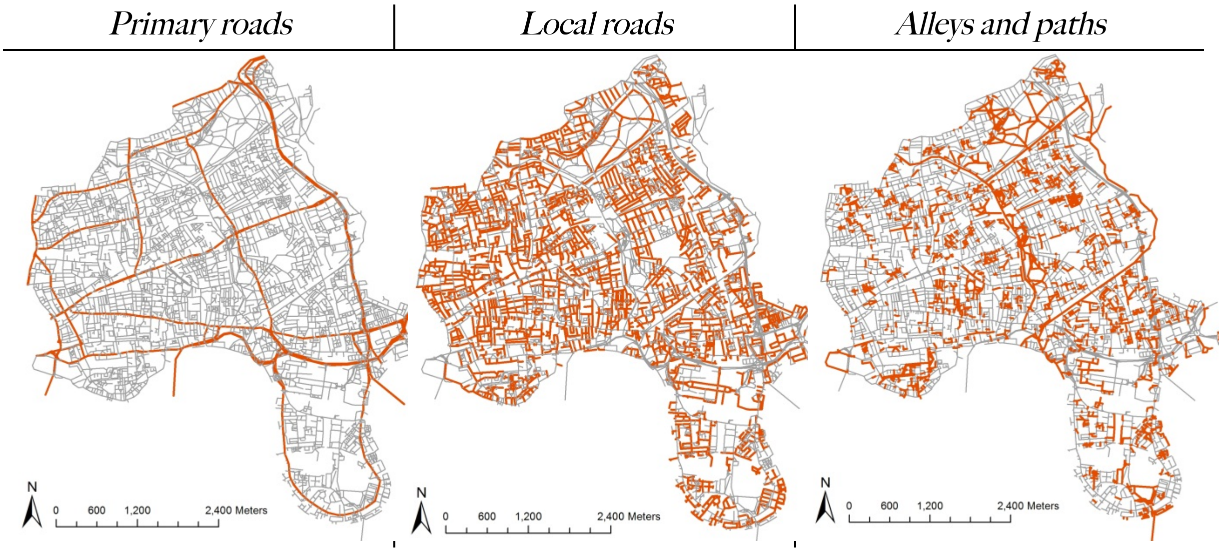
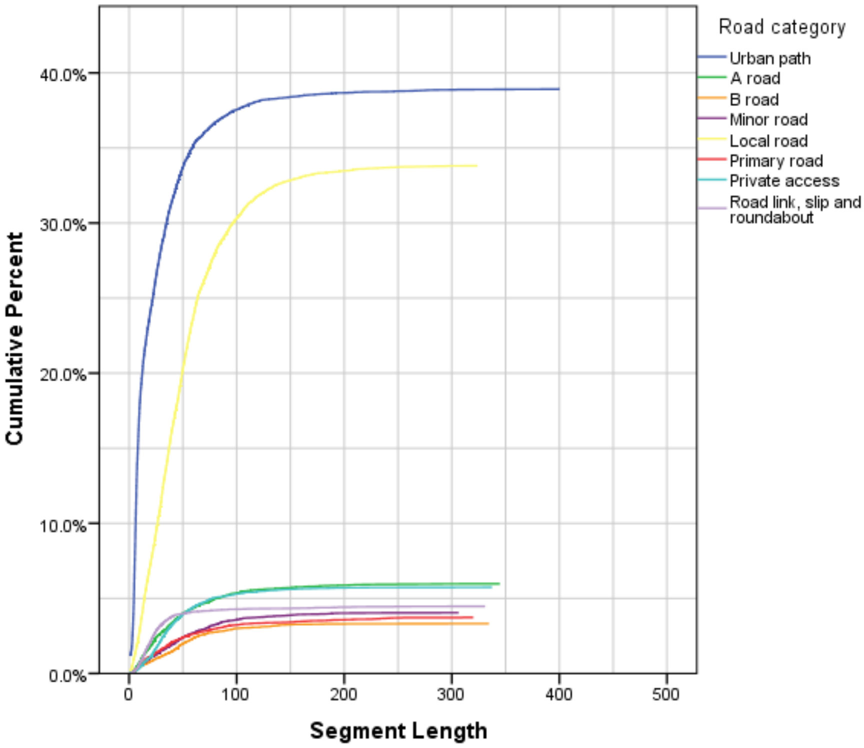


Figure 16: Cumulative percentage of street network length grouped according to road category



Crime rates were computed for every category of road according to drug production, supply and possession crime types, see **Table 8**. If L_k is the total length of street network for a given street category k and C_i is the count of crime incidents for drug crime type i that occurred on the corresponding street category k, then the rate of drug crime per kilometre of network is defined as:

$$\mathrm{R}_{ik} = \frac{C_{ik}}{L_k} \times 10 \tag{5.3}$$

From **Table 8,** it can be seen that from the 93 cases of drug production as predicted, the private roads have the highest rate of crime per kilometre of network followed by other categories of roads with almost equal rates. The urban pathways category of road had the lowest rate of drug production.

With the drug supply incidents, the highest rate of crime has B type of roads, followed by local road and private road categories. Also these road categories have the highest number of crime counts per single street segment. That is, repeated incidents of drug dealing were observed at roads of local significance, implicitly indicating potential drug market places. When rates are compared to standard error bars, only local roads and urban paths had a reliable estimation.

In the case of drug possession incidents some roads had more than 300 repeated incidents per single street segment. Here also the highest rate of crime was associated with roads of local significance – B type of roads, followed by local roads. However, only local roads, private roads and urban paths are accurate according to the error bar graph. The standard errors associated with the estimates are again large.

Overall, the descriptive statistics suggests that the streets that facilitate the connection between local significant places are more associated with drug crime than the roads that facilitate regional movement in the borough, however, the standard errors associated with the estimates indicate that there is considerable variation across streets.

Table 8: Crime rates for drug production (n = 93), supply (n = 732) and possession (n = 5780) offences per kilometre of network and according to road types (rates reported to one decimal place)

Road type	**Total length** (Km)	**Production**		**Supply**		**Possession**	
		Drug crime **Count** (Maximum *count* per segment)	**Rate** of crime count per km	Drug crime **Count** (Maximum *count* per segment)	**Rate** of crime count per km	Drug crime **Count** (Maximum *count* per segment)	**Rate** of crime count per km
A road	38	7(3)	1.8	27(6)	7.1	245(45)	64.4
Primary road	27	4(1)	1.5	21(9)	7.8	292(42)	108.1
B road	22	4(1)	1.8	108(32)	**49.0**	608(104)	**276.3**
Minor road	28	5(1)	1.8	19(4)	6.8	231(24)	82.5
Local road	226	43(1)	1.9	383(18)	16.9	2665(312)	117.9
Private road	36	9(2)	**2.5**	64(13)	17.8	377(55)	104.7
Road link, slip	18	3(2)	1.6	5(1)	2.8	52(10)	28.8
Urban pathways	130	17(2)	1.3	102(9)	7.8	1274(387)	98.0

5.3.3.2 Street Segment Connectivity and Drug Crime

Street segment *connectivity* is a topological feature of the street network. It restricts or permits movement along the network. For every street segment in the case study area this *index* quantifies the direct number of street segments each street is directly connected to. It has been claimed (Jacobs 1961) that intensified patterns of street connections encourage local movement. Thus, street junctions where two or more roads intersect are considered more permeable than are streets that lead to dead ends. The map in **Figure 17** shows how the index of first order connectivity varies across the case study area. Street segments with five to six connections are important street intersections that connect several roads hence can be considered quite permeable at a local scale. The street segments with one connection and those leading to one connection are dead ends and are considered to have the lowest degree of permeability in the network. However, it should be noted that in some cases, particularly in organic grids, street segments with two or more connections could also indirectly lead to dead ends (Hillier and Sahbaz 2009).

The ECDF in **Figure 18a** shows that 60% of street segments are connected to three or more street segments. The longest streets (**Figure 18b**) are well connected (4 and 6 connections). Also, segments with one connection tend to be the shortest in the network. Thus, overall longer street segments appear to be better connected than are shorter ones.

To examine the influence of connectivity on crime risk, the rate of crime per kilometre of road grouped according to the street segment connectivity value was calculated the same way as in **Equation 1**. **Table 9** shows the crime rates for drug production, supply and possession. From the overall trend it can be seen that drug production cases tend to happen more on less connected street segments (up to 3 connections) and drug possession cases have a tendency to occur on better connected segments (5 and 6 connections). With drug supply cases, the rates are somewhat similar across the connectivity indices peaking for segments with 1 and 5 connections.

Figure 17: Street network coloured according to first order connectivity index, sample size n = 13,153 segments

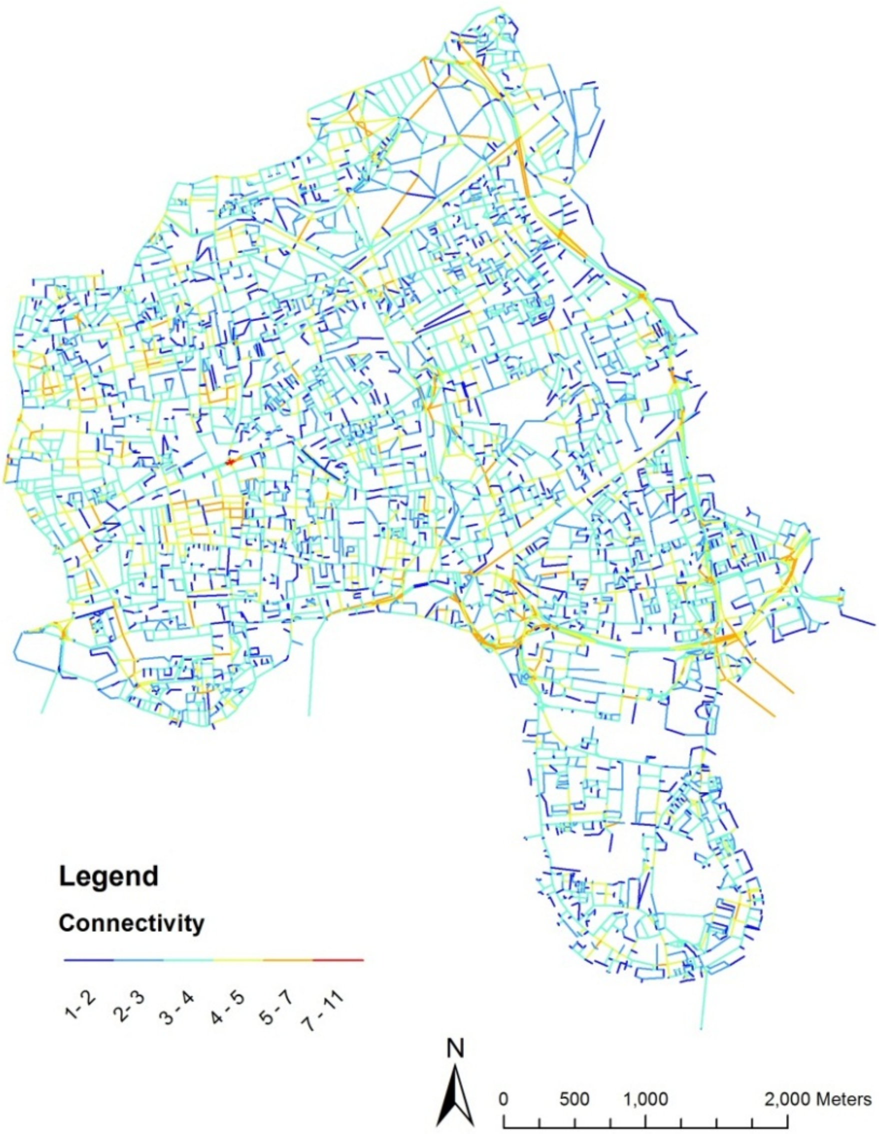
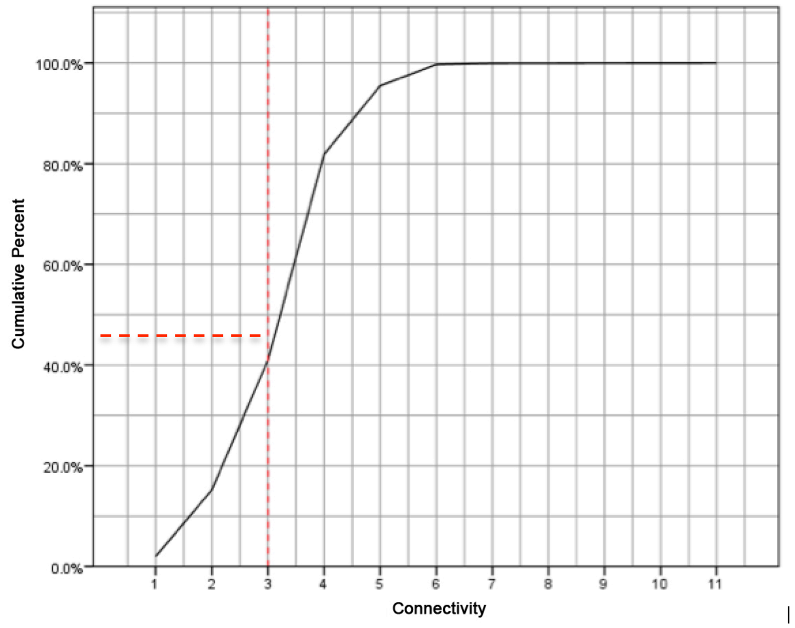


Figure 18: Cumulative percentage of street network according to first order connectivity index (a) and cumulative percentage of street network length grouped according to connectivity index (b), sample size n = 13,153 segments

a)



b)

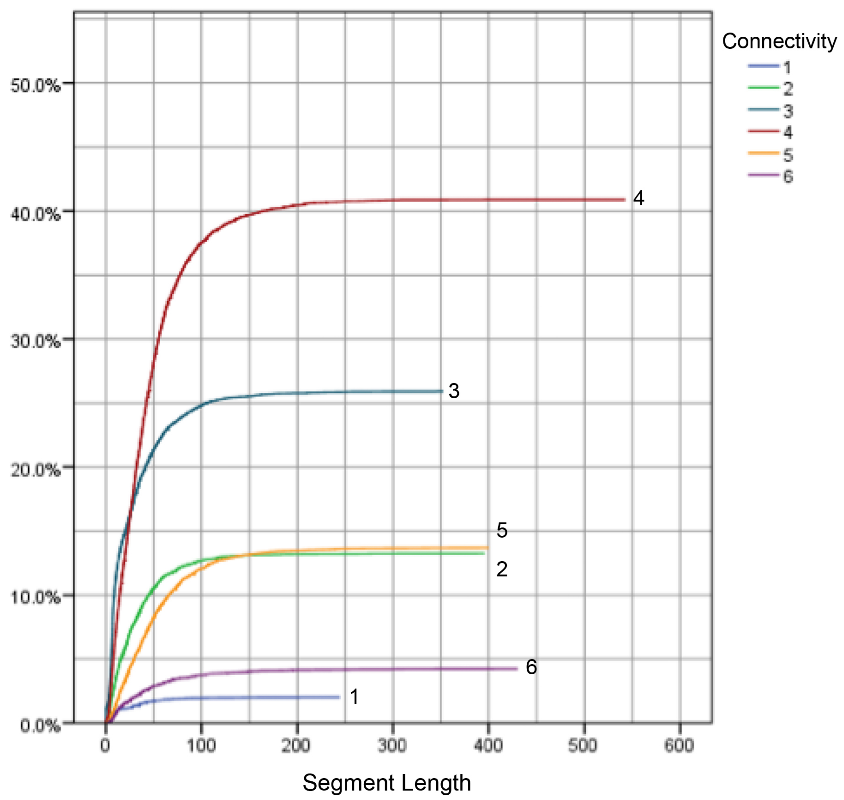


Table 9: Crime rates for drug production (n = 93), supply (n = 732) and possession (n = 5780) offences per kilometre of network and according to connectivity count (rates reported to one decimal place)

Connectivity count	Total length	Production		Supply		Possession	
		Drug **count** (Maximum count per segment)	**Rate** of crime per km	Drug **count** (Maximum count per segment)	**Rate** of crime per km	Drug **count** (Maximum count per segment)	**Rate** crime per km
1	7.40	7(2)	**9.5**	14(6)	**18.9**	85(7)	114.8
2	57.80	8(1)	1.4	77(7)	13.3	1097(387)	**189.7**
3	95.80	21(2)	2.2	127(13)	13.2	1074(312)	112.1
4	236.00	38(2)	1.6	312(15)	13.2	2316(104)	98.1
5	94.00	16(3)	1.7	165(32)	17.6	1020(98)	108.5
6	27.00	3(1)	1.1	37(18)	13.7	188(17)	69.6
7	1.40	0	0.0	0	0.0	0	0.0
8	0.03	0	0.0	0	0.0	0	0.0
9	0.13	0	0.0	0	0.0	0	0.0
10	0.07	0	0.0	0	0.0	0	0.0
11	0.05	0	0.0	0	0.0	0	0.0

5.3.3.4 Configurational Permeability and Drug Crime

In order to compute the probabilistic distribution of movement volumes across the street network, a *segment* map of the borough with the 4.5 km buffer was used. Using Depthmap software (Turner, 2001) *angular segment analysis* was performed for a series of local and regional metric radii (r800, 1200 and 4000) and the values of *through movement* (choice) and *to movement* (integration) were obtained for corresponding radii, see **Figure 19**. Since no drug crime data were available for the buffer area of 4.5km, the space syntax values for the street network within the administrative boundaries of the Tower Hamlets borough were extracted for the purposes of analysis. Thus, **Figure 20** shows the final area (13,153 segments) with corresponding permeability levels that were examined in relation to drug crime.

Figure 19: Segment angular analysis of to-movement permeability for 2400 radius, output from Depthmap software, values according to *natural break* distribution

Figure 20: Configurational permiability of the street network for two types of movement grouped according to local and regional scales of movement (sample size n = 13,153 segments, values according to a *natural break* distribution)

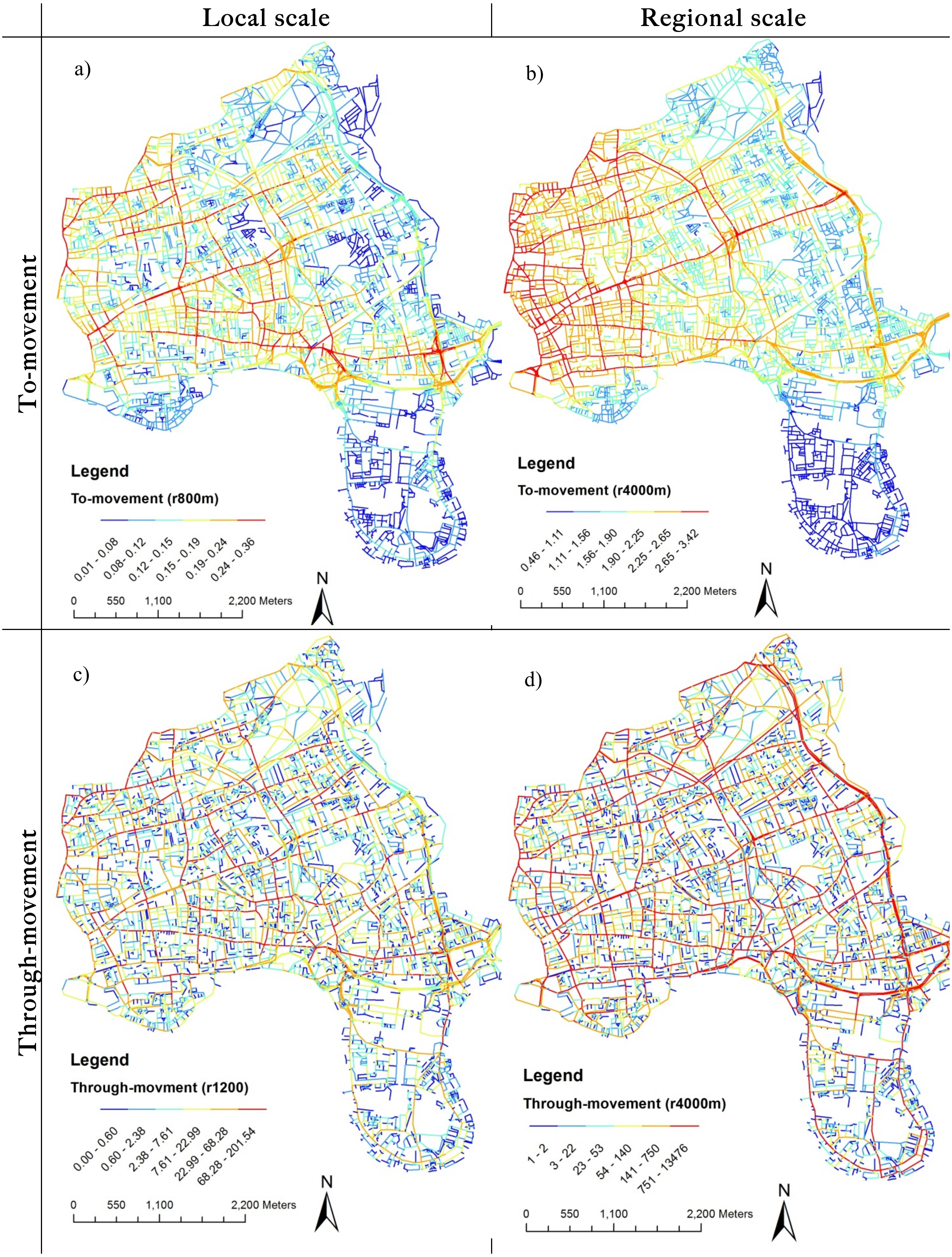
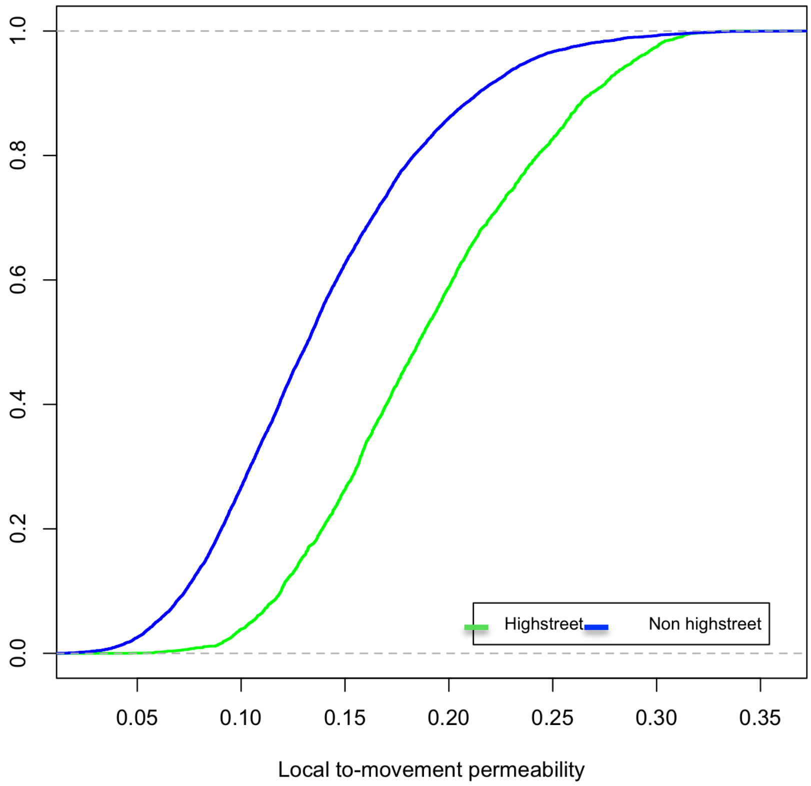


Figure 20 illustrates two paires of local and regional movement permeability across the street network, where first, every street segment is treated as a destination and consequently the to-movement potentials are calculated for corresponding segments, and, in the second analyis, the same segments are treated as spaces that are travelled through during the movement from origin to destination, thus through-movement potential is quantified. The permeability level is colour coded and decreases from red (most permeable) to blue (least permeable). Two movement scales were considered: *local* that is more associated with pedestrian movement within a 10 minute walk (corresponding to 800 meter for the London area) and *regional* – related to vehicular movement or 50 minute walking distance (corresponding to 4000m for the London area).

The map of local scale *to-movement* permeability (**Figure 20a**) highlights the potential local centres of activity. When the map is compared to the existing locations of high streets (see **Figure 21**) similarities emerge. **Figure 21** shows that from all street segments, those that are coded as high streets are located on more permeable segments.

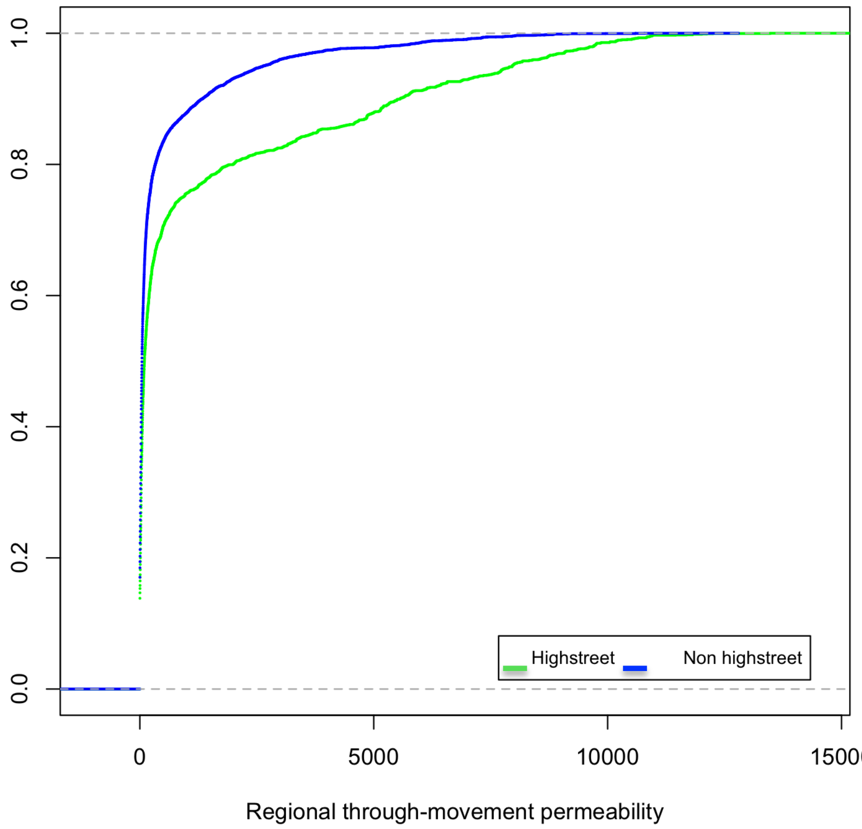
Figure 21: The cumulative distribution of *local to-movement* permeability disaggregated according to high street and non-high street segments, sample size n = 13,153 segments



On the map of regional scale *to-movement* permeability (**Figure 20b**) the core distribution of highly permeable segments is skewed to the West, where the borough borders with London's central activity zone leading to the city center.

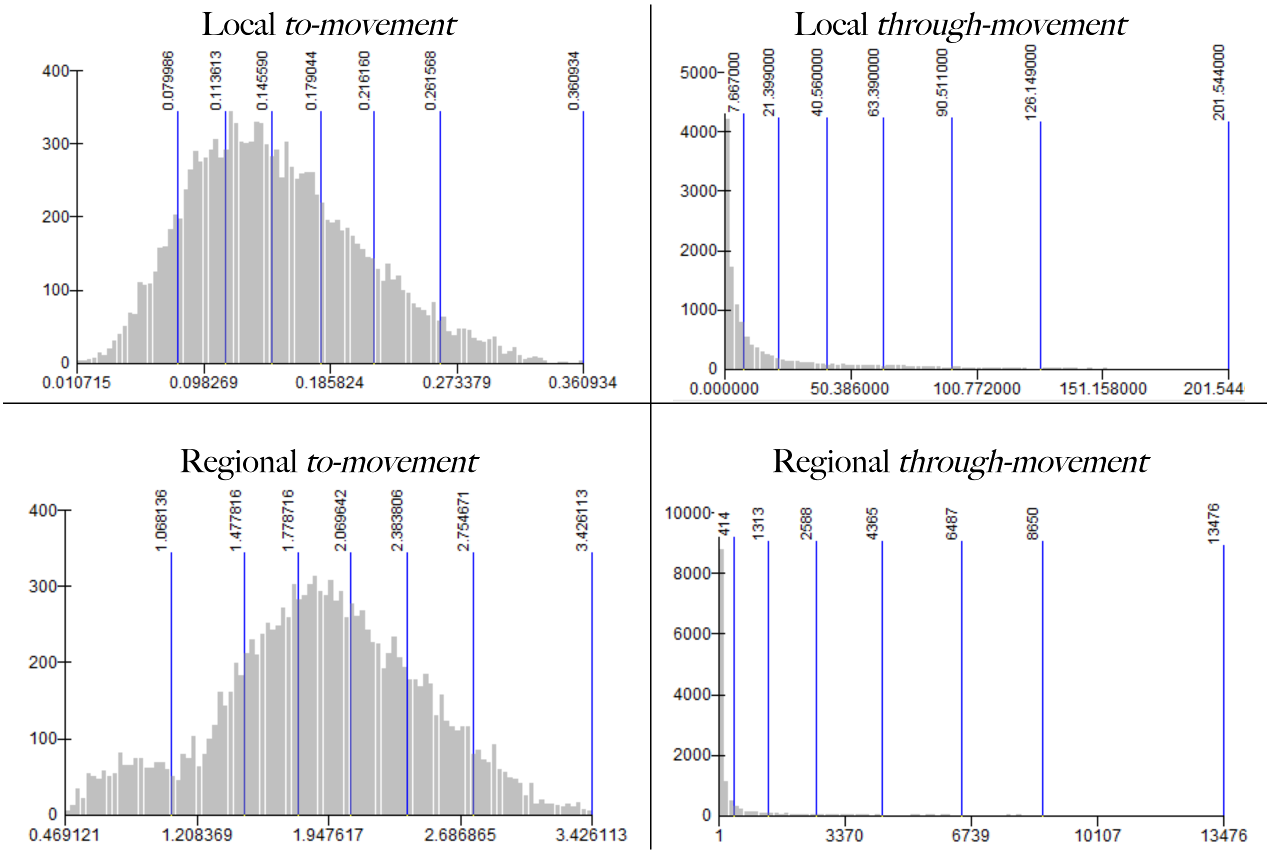
Through-movement permeability provides a global measure of movement volumes, since it identifies those streets that are located within the shortest routes from all origins to all destinations. Thus, the maximum volume of potential movement passing through the segment can be calculated at the intra-city scale of movement (**Figure 20 d**). **Figure 22** shows that of non-high street segments are less permeable than high street segments. Thus, high streets represent highly permeable roads.

Figure 22: The cumulative distribution of *regional through-movement* permeability disaggregated according to high street and non-high street segments, sample size n = 13,153 segments



These two types of movement were further examined in relation to drug crime. Since permeability measures are continuous variables with no defined intervals and a large variance, Jenks natural break method was used (Jenks and Caspall 1971). The values of permeability were aggregated according to 7 ranges. Through an iterative process the algorithm grouped values according to the natural breaks that were inherent in the variable. It identified clusters of similar values, by maximising the difference - the large change in unit value between the ranges. Thus, the ranges were not equal in their frequencies of similar values. The odd number of ranges was chosen to have a central interval and because it ensured that enough detail was captured in the variation of the variable. **Figure 23** shows the classification of permeability for two scales grouped according to the type of movement. It can be seen that to-movement permeability follows normal distibution, while through-movement permeability is quite skewed.

Figure 23: Classification of permeability variable according to Jenks natural break method, 13,153 segments were aggregated to 7 ranges



Next, the density of drug crime incidents per street network length was calculated according to variations in local and regional to-movement and through-movement permeability. It can be seen that highest densities of drug supply and possession crime are associated with very permeable streets that are accessible as a destination both at local and regional scales of movement, see **Table 10** and **Table 11.** With drug production crime, the highest density of crime is situated on the segments that are permeable only at a local scale of movement. For through-movement permeability, the densities are somewhat similar. Overall, the highest densities are on those streets that are permeable for through-movement mainly at local scale of movement; see **Table 12** and **Table 13**.

Table 10: Density of drug crime incidents per street network unit length according to variation in ***local to-movement permeability*** level

DRUG PRODUCTION CASES

N	Local to-movement range	Frequency of all segments	Total length (Km)	Count of incidents	Density per street network km
1.	0.01<local to-movement <0.07	992	35.8	17(2)	**0.47**
2.	0.07 < local to-movement <0.11	2,795	102.3	18(1)	0.17
3.	0.11< local to-movement <0.145	3,099	118.9	17(2)	0.14
4.	0.145< local to-movement <0.179	2,576	102.3	21(2)	0.20
5.	0.179< local to-movement <0.216	1,893	82.0	12(2)	0.14
6.	0.216< local to-movement <0.261	1,256	54.3	11(3)	0.20
7.	0.261< local to-movement <0.360	601	22.6	5(1)	0.22
	Total	13,153	521.0	93	

DRUG SUPPLY CASES

N	Local to-movement range	Frequency of all segments	Total length (Km)	Count of incidents	Density per street network km
1.	0.01<local to-movement <0.07	992	35.8	9(2)	0.25
2.	0.07 < local to-movement <0.11	2,795	102.3	84(6)	0.82
3.	0.11< local to-movement <0.145	3,099	118.9	173(13)	1.45
4.	0.145< local to-movement <0.179	2,576	102.3	166(18)	1.62
5.	0.179< local to-movement <0.216	1,893	82.0	128(15)	1.56
6.	0.216< local to-movement <0.261	1,256	54.3	105(14)	1.93
7.	0.261< local to-movement <0.360	601	22.6	59(32)	**2.61**
	Total	13,153	521.0	732	

DRUG POSSESSION CASES

N	Local to-movement range	Frequency of all segments	Total length (Km)	Count of incidents	Density per street network km
1.	0.01<local to-movement <0.07	992	35.8	141(9)	3.93
2.	0.07 < local to-movement <0.11	2,795	102.3	718(103)	7.01
3.	0.11< local to-movement <0.145	3,099	118.9	1192(312)	10.02
4.	0.145< local to-movement <0.179	2,576	102.3	1471(387)	14.37
5.	0.179< local to-movement <0.216	1,893	82.0	1033(67)	12.59
6.	0.216< local to-movement <0.261	1,256	54.3	902(104)	**16.61**
7.	0.261< local to-movement <0.360	601	22.6	323(24)	14.29
	Total	13,153	521.0	5780	

Table 11: Density of drug crime incidents per street network unit length according to variation in ***regional to-movement permeability*** level

DRUG PRODUCTION CASES

N	Regional to-movement range	Frequency of all segments	Total length (Km)	Count of incidents	Density per street network km
1.	0.01<regional to-movement <1.06	377	42.2	10(2)	**0.23**
2.	1.06 < regional to-movement <1.47	1,559	55.4	11(1)	0.19
3.	1.47< regional to-movement <1.77	2,513	88.2	13(1)	0.14
4.	1.77< regional to-movement <2.06	2,876	106.0	17(2)	0.16
5.	2.06< regional to-movement <2.38	2,449	103.4	16(2)	0.15
6.	2.38< regional to-movement <0.75	1,834	86.8	19(3)	0.21
7.	0.75< regional to-movement <0.34	827	36.6	7(1)	0.19
	Total	13,153	521.0	93	

DRUG SUPPLY CASES

N	Regional to-movement range	Frequency of all segments	Total length (Km)	Count of incidents	Density per street network km
1.	0.01<regional to-movement <1.06	377	42.2	23(3)	0.54
2.	1.06 < regional to-movement <1.47	1,559	55.4	29(8)	0.52
3.	1.47< regional to-movement <1.77	2,513	88.2	85(9)	0.96
4.	1.77< regional to-movement <2.06	2,876	106.0	113(14)	1.06
5.	2.06< regional to-movement <2.38	2,449	103.4	188(13)	1.81
6.	2.38< regional to-movement <0.75	1,834	86.8	196(32)	2.25
7.	0.75< regional to-movement <0.34	827	36.6	98(14)	**2.67**
	Total	13,153	521.0	732	

DRUG POSSESSION CASES

N	Regional to-movement range	Frequency of all segments	Total length (Km)	Count of incidents	Density per street network km
1.	0.01<regional to-movement <1.06	377	42.2	228(13)	5.40
2.	1.06 < regional to-movement <1.47	1,559	55.4	269(18)	4.85
3.	1.47< regional to-movement <1.77	2,513	88.2	573(103)	6.49
4.	1.77< regional to-movement <2.06	2,876	106.0	1027(312)	9.68
5.	2.06< regional to-movement <2.38	2,449	103.4	1485(387)	14.36
6.	2.38< regional to-movement <0.75	1,834	86.8	1265(67)	14.57
7.	0.75< regional to-movement <0.34	827	36.6	932(104)	**25.46**
	Total	13,153	521.0	5780	

Table 12: Density of drug crime incidents per street network unit length according to variation in ***local through-movement permeability*** level

DRUG PRODUCTION CASES

N	Local through-movement range	Frequency of all segments	Total length (Km)	Count of incidents	Density per street network km
1.	0.0<local through-movement <7.6	6258	228.9	39(2)	0.17
2.	7.6 < local through-movement <21.3	2309	105.6	15(1)	0.14
3.	21.3< local through-movement <40.5	1153	55.9	6(1)	0.10
4.	40.5< local through-movement <63.3	795	36.0	4(1)	0.11
5.	63.3< local through-movement <90.5	630	28.1	7(3)	0.24
6.	90.5< local through-movement <126.1	353	14.4	5(1)	0.34
7.	126.1< local through-movement <201.5	236	7.6	3(1)	**0.39**
	Total	13,153	521.0	93	

DRUG SUPPLY CASES

N	Local through-movement range	Frequency of all segments	Total length (Km)	Count of incidents	Density per street network km
1.	0.0<local through-movement <7.6	6258	228.9	288(13)	1.25
2.	7.6 < local through-movement <21.3	2309	105.6	143(18)	1.35
3.	21.3< local through-movement <40.5	1153	55.9	68(14)	1.21
4.	40.5< local through-movement <63.3	795	36.0	82(15)	**2.27**
5.	63.3< local through-movement <90.5	630	28.1	63(32)	2.24
6.	90.5< local through-movement <126.1	353	14.4	23(4)	1.59
7.	126.1< local through-movement <201.5	236	7.6	17(2)	2.23
	Total	13,153	521.0	732	

DRUG POSSESSION CASES

N	Local through-movement range	Frequency of all segments	Total length (Km)	Count of incidents	Density per street network km
1.	0.0<local through-movement <7.6	6258	228.9	2384(387)	10.41
2.	7.6 < local through-movement <21.3	2309	105.6	915(67)	8.66
3.	21.3< local through-movement <40.5	1153	55.9	631(64)	11.28
4.	40.5< local through-movement <63.3	795	36.0	517(104)	14.36
5.	63.3< local through-movement <90.5	630	28.1	374(45)	13.30
6.	90.5< local through-movement <126.1	353	14.4	158(25)	10.97
7.	126.1< local through-movement <201.5	236	7.6	197(24)	**25.92**
	Total	13,153	521.0	5780	

Table 13: Density of drug crime incidents per street network unit length according to variation in ***regional through-movement permeability*** level

DRUG PRODUCTION CASES

N	Regional through-movement range	Frequency of all segments	Total length (Km)	Count of incidents	Density per street network km
1.	0 <regional through-movement <414	9009	338.8	58(2)	0.17
2.	414 < regional through-movement <1313	1056	541.2	5(1)	0.01
3.	1313< regional through-movement <2588	645	358.1	8(2)	**0.02**
4.	2588< regional through-movement <4365	405	215.2	1(1)	0.01
5.	4365< regional through-movement <6487	305	132.7	3(3)	**0.02**
6.	6487< regional through-movement <8650	196	851.5	4(1)	0.01
7.	8650< regional through-movement <13476	130	541.7	1(1)	0.01
	Total	13,153	521.0	93	

DRUG SUPPLY CASES

N	Regional through-movement range	Frequency of all segments	Total length (Km)	Count of incidents	Density per street network km
1.	0 <regional through-movement <414	9009	338.8	485(18)	**1.43**
2.	414 < regional through-movement <1313	1056	541.2	51(10)	0.09
3.	1313< regional through-movement <2588	645	358.1	89(32)	0.24
4.	2588< regional through-movement <4365	405	215.2	26(9)	0.12
5.	4365< regional through-movement <6487	305	132.7	17(6)	0.12
6.	6487< regional through-movement <8650	196	851.5	7(2)	0.01
7.	8650< regional through-movement <13476	130	541.7	10(2)	0.01
	Total	13,153	521.0	732	

DRUG POSSESSION CASES

N	Regional through-movement range	Frequency of all segments	Total length (Km)	Count of incidents	Density per street network km
1.	0 <regional through-movement <414	9009	338.8	3646(387)	**10.76**
2.	414 < regional through-movement <1313	1056	541.2	393(30)	0.72
3.	1313< regional through-movement <2588	645	358.1	499(104)	1.39
4.	2588< regional through-movement <4365	405	215.2	212(27)	0.98
5.	4365< regional through-movement <6487	305	132.7	93(10)	0.70
6.	6487< regional through-movement <8650	196	851.5	218(42)	0.25
7.	8650< regional through-movement <13476	130	541.7	132(25)	0.24
	Total	13,153	521.0	5780	

5.3.3.5 High Street and Drug Crime

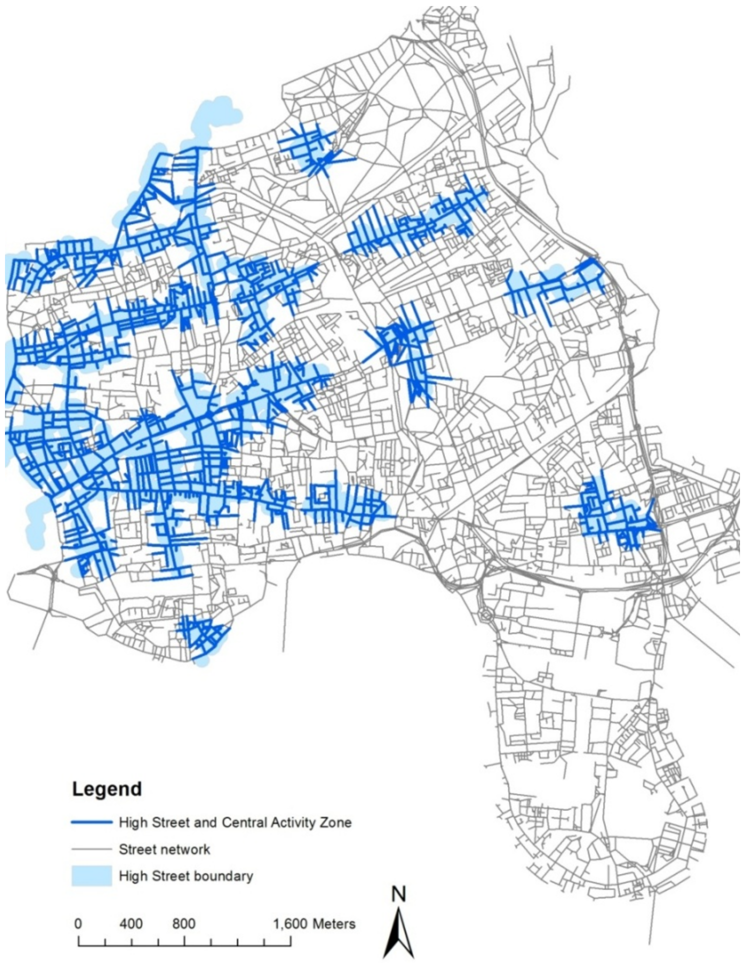
The high street was chosen as an independent variable, based on the rationale that it attracts large flows of movement and that intuitively everyone can distinguish between the high street and ordinary roads. Moreover, for the police it is easy to use the high street as a proxy- an anchoring point from which they can navigate adjacent residential neighbourhoods. It is hypothesised that since people can intuitively distinguish between high streets and ordinary streets, drug dealers may use this spatial information to position themselves in some relation to the high street.

High streets are very common road in the UK. Usually, they are well positioned in the surrounding neighbourhood and are very permeable for local residents. The main characteristic of this type of street is its great mix of different retail land uses located along a linear route of street segments, well-connected by public transport. This type of street attracts a large number of pedestrian movements in comparison to the rest of the neighbourhood. Often the same high street segment can also be an important traffic route. However, a recent report (Gort Scott and UCL 2010) showed that while 6% of London's street network is occupied by high streets, there is no official definition of the high street as a road typology in Ordinance Survey. According to this classification, some high streets are categorised under primary streets or 'A' type of streets or local streets.

Consequently, in this study recent research on the high streets of London a study by Carmona and colleagues (Gort Scott and UCL 2010) was used as a guide to define the high streets in the case study area. The authors of the report state that they identified high street segments with 95% accuracy based on land use datasets and field observations. According to their methodology, the minimum length of the high street adopted was 350 metres. Also, large enclosed shopping centres were excluded from the sample. The report made a distinction between high streets and agglomerations of streets consisting of mixed uses geographically located near the city centre. Such groups of streets were defined as London's Central Activity Zones (CAZ). In the current research both types of street segments - defined as high streets and counted as CAZ - were included in the analysis under the *high street* category. The reasoning for this was that if a drug dealer uses 'active or busy' street segments as a proxy for choosing drug dealing sites, for them both types of street have similar operating conditions, i.e. large flows of potential customers passing by.

Figure 24 shows the high street segments in comparison to the rest of the network, while **Table 13** provides some descriptive statistics. It shows that 23% of the street network of the case study area is classified as high street. This proportion includes CAZ's part of the network as well. On average, the mean length of the high street segments was longer than the rest of the network. The density of crime counts was calculated for high street and non-high-street segments using **equation 1**. As expected, the density of drug supply and possession cases were higher for high street segments than the rest of the network, and were dissimilar to the density of production cases, the latter being higher on non-high street roads, see **Table 14**.

Figure 24: High streets map of case study area



This map was created based on study conducted by Gort Scott and UCL (2010).

Table 13: The fraction of high street segments in comparison to the rest of the network with corresponding maximum and mean segment length in metres

Road type	Total **length** (Km)	**Fraction** from the whole network (%)	**Maximum** segment length (m)	**Mean** segment length (m)	**Median** segment length (m)
High street	120	23	294	43	34
None high street	401	77	597	39	26
All street network	521	100	597	40	28

Table 14: Density of drug crime within 100meter buffer zone from High street

Drug crime type	**Crime count**		**Total length** of crime prone segments (km)		**Density** of crime per km	
	High street	*Elsewhere*	*High street*	*Elsewhere*	*High street*	*Elsewhere*
Production	51	42	4.5	3.2	11.3	**13.1**
Supply	479	253	18.8	10.7	**25.5**	23.6
Possession	3839	1941	60.4	43.8	**63.5**	44.3

Further analysis disaggregated the high street into smaller areas. That is, a distinction was made between the main high street area, which is commonly linear and has a chain of retail facilities, and the streets that are perpendicularly adjacent to the high street. It was hypothesised that high street segments boost the risk of drug dealing, but that adjacent street segments would be more risky. First, through Google map street view all high street segments were visually inspected and assessed as to whether or not they looked like the main high street area by taking into account the presence of shops, high end offices and public transport. If a segment was identified as a high street it was binary coded as 1 (0 otherwise). Second, all the segments that were both located within the high street boundary were defined by researchers (Gort Scott and UCL 2010) and were adjacent to the high street were coded as 1 using a second variable. The rest of the network was coded as 0. **Figure 25** shows the disaggregated map of the high street. It can be seen that 5% of the street network was identified as belonging to the main high street and the adjacent segments comprised 20% of the street network. **Figure 26** shows that at the local scale of movement, high street segments are the most permeable in the network (Figure 20a) and the street segments that are adjacent to high street overall are the second most permeable streets on the network. However, at the regional scale, both high streets and adjacent streets are not the most permeable segments in the network.

Figure 25: High streets and adjacent to high street segments, sample size n = 13,153 segments

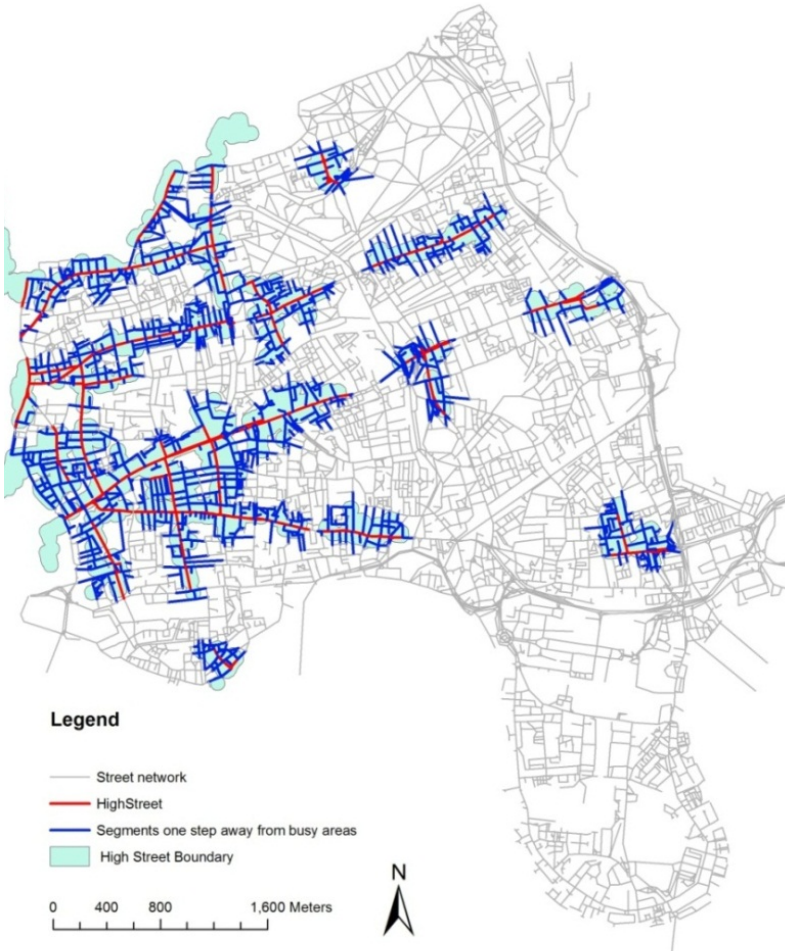
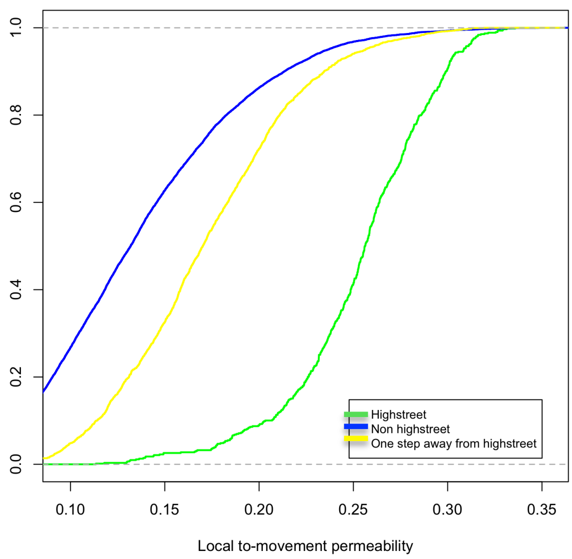
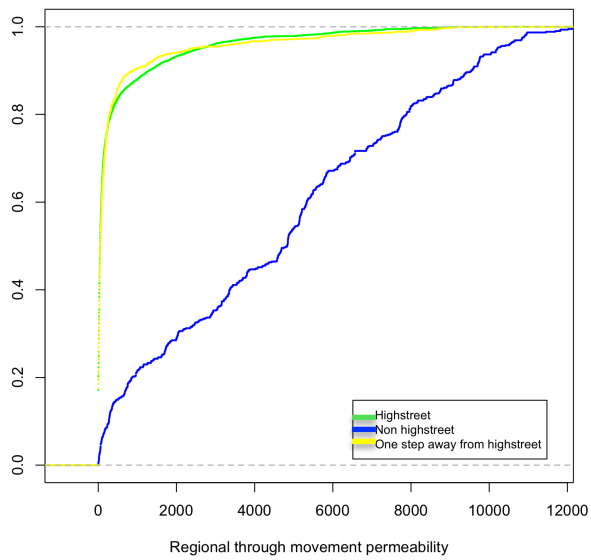


Figure 26: Cumulative percentage of the local to-movement and regional through-movement street network permeability grouped according to *high street, adjacent to high street* and *elsewhere* categories, sample size n = 13,153 segments

a)



b)



The density of drug crime was again calculated for three different categories of streets: high streets, those adjacent to them and those located elsewhere (**Table 14** and **Table 15**). First it can be seen that segments adjacent to the high street had more repeated incidents of drug dealing than the high street. In terms of crime density it can be seen that the densities of crime per kilometre of network decrease gradually from high street to the adjacent streets and to the rest of the neighbourhood. However, it should be noted that proportionally the total length of high street is 4 times less than the total length of adjacent street segments. Moreover, in terms of raw crime counts more crime is associated with the adjacent street segments than the high street itself. Since the estimated density of crime counts depends on the length of segments, it is not surprising that the densities of crime per kilometre of network are somewhat misrepresented. More accurate estimations were produced from the regression model.

Table 14: High street segments in comparison to the rest of the network

Road type	Total **length** (Km)	**Fraction** from the whole network (%)	**Maximum** segment length (m)	**Mean** segment length (m)	**Median** segment length (m)
High street	23	4.4	233	37	30
Segments adjacent to high street	97	18.6	294	45	35
None high street	401	77.0	597	39	28
All street network	521	100.0			

Table 15: Density of drug crime for *high street*, *adjacent to high street* and *elsewhere* categories

Drug crime type	**Crime count** (Maximum *count* per segment)			**Total length** of crime prone segments (km)			**Density** of crime per km		
	On high street	*Adjacent* to high street	*Elsewhere*	*On* high street	*Adjacent* to high street	*Else where*	*On* high street	*Adjacent* to high street	*Else where*
Production	8(1)	20(1)	65(3)	23	97	401	**0.34**	0.20	0.16
Supply	75(14)	297(32)	360(15)				**3.26**	3.06	0.89
Possession	686(104)	1884(312)	3210(387)				**29.82**	19.42	8.00

5.4 Statistical background

5.4.1 Statistical modelling and diagnostic methods

In order to test the hypotheses set out in **Table 1** (p.148), mainly to establish a functional relationship between drug crime and urban characteristics of the environment, a series of regression analyses were conducted. The basic regression model is defined as:

$$y_i = \beta_1 x_i + \beta_0 + \varepsilon \,; \quad i = 1, \ldots, n \qquad (3)$$

where, $\boldsymbol{y}$ is the dependent variable,

$\boldsymbol{x}$ is the independent variable,

$\boldsymbol{\beta}$ is the unknonw parameter

$\boldsymbol{\varepsilon}$ error term.

In this chapter, the dependent variable was the count of drug crime aggregated to street segments and the independent or predictor variables were the level of street permeability. In addition, high streets were included as a proxy for permeable and busy streets. Street segment length was included as a control variable to account for the fact that these would be more opportunities for crime on longer street segments. Prior to regression analysis, several diagnostic tests were performed in order to evaluate the dependent and independent variables, to see if they met the assumptions of the regression model, and consequently to decide what type of regression model(s) to use for hypothesis testing. **Table 16** summarises the diagnostic tests conducted for the corresponding variables. The following section describes every test separately and presents the corresponding results obtained using CrimeStat IV software (Levine, 2010).

Table 16: Summary of diagnostic tests for dependent and predictor variables

Variable type	Diagnostic test used
Dependent	Test of skewed distribution Test of spatial autocorrelation
Predictive	Test of multicollinearity

For ordinary least square linear regression, a number of important assumptions regarding the dependent variable need to be met. If violated, the regression results will be biased and inaccurate. Four assumptions should be considered:

1. The dependent variable should have a normal or close to normal distribution of values.
2. Regression error term be independent and normally distributed.
3. Additionally, the residual error (the difference between observed and predicted values) should be constant for the count variable: it increases with large counts having higher estimation errors than for counts with few incidents.
4. Furthermore, given the spatial structure of crime data where the observations are interrelated with similar values clustered together, the error terms tend to be highly correlated, which biases the model and produces underestimated or overestimated coefficients and standard errors.

In the case of crime counts with a highly skewed distribution the assumptions may be violated. The ***tests of skewness*** and ***autocorrelation*** test these assumptions.

In the statistical model, all independent or predictor variables should be statistically independent from each other. That is, their contribution in explaining the variance in the dependent variable should be unique. When two or more predictive variables are correlated, the estimated standard errors of the model coefficient can be inaccurate. This issue is referred to as multicollinearity, when two correlated independent variables are included in a single model, often neither appears significant, in comparison to a model when a single variable is included and it is significant. In other cases, both might be significant, but will acquire reverse signs (from positive to negative or vice versa). Both cases of multicollinearity are demonstrated using concrete examples in the text below. The ***tolerance test*** examines multicollinearity between the independent variables.

Test of skewness: skewness describes the asymmetry of a distribution around the mean. The presence of skewness violates the assumptions of normal statistical models where it is assumed that the dependent variable follows normal Gaussian distribution (Levine et al.; 2010). As a result, the high values of the dependent variable will be underestimated and low values – overestimated by the normal model. Commonly crime count data have a positively skewed distribution when measured at the small area level. Two diagnostic tests of skewness were conducted. The first is the g test (Levine et al.; 2010) and the second involved comparing the ratio of variance to mean.

The g test measures the degree of asymmetry of a distribution around its mean and is defined as:

$$g = \frac{n}{(n-1)(n-2)} \sum_i [(x_i - \bar{x})/s]^3 \tag{4}$$

where $\bar{x}$ is the mean of a variable x and s is the standard deviation of a sample with the size n. The standard error of skewness (SES) is defined as (Levine et al., 2010):

$$\mathrm{SES} = \sqrt{\frac{6}{\mathrm{n}}} \tag{5}$$

And a Z test is calculated as:

$$Z(g) = \frac{g}{SES} \tag{6}$$

If the Z test is positive and greater than 1.96, this indicates significant skewness in the data (of the p≤.05 level) and that the majority of values are below the mean with a long tail of distribution near high range values.

The second diagnostic test of skewness involves calculating the ratio of the variance of the dependent variable divided by its mean. Ratio's greater than 2:1 indicate the presence of skewness in dependent variable.

Test of autocorrelation: A diagnostic test of statistical independence of the aggregated crime counts per street segment (i.e. dependent variable) was performed. Here, the test examines the spread of crime frequencies, and whether or not there is a spatial interaction between adjacent crime values. The null hypothesis is that there is no spatial relationship between one location of drug dealing and any other. The presence of spatial interaction known as *spatial autocorrelation* indicates that the crime locations at the street segment level are interrelated and statistically dependent. In geography, spatial autocorrelation is calculated using *correlations* (when the variable is correlated with itself throughout the space), *probabilities* (the likelihood of an event occurring in the area, given the existence of a similar event in a nearby area) or *similarities* (the degree of similarity (dissimilarity) of events in neighbouring areas). In this research, the latter definition of autocorrelation was used to compute Moran's I (Anselin; 1995) statistics. This diagnostic test shows how similar or dissimilar are the frequencies of a continuous variable for adjacent locations and is defined as:

$$I = \frac{N \sum_i \sum_j w_{ij}(x_i - X)(x_j - X)}{(\sum_j \sum_j w_{ij}) \sum_i (x_i - X)^2} \qquad (7)$$

where N is the number of crime events, x_i is the crime frequency at location i and x_j is the crime frequency at any location j. X is the mean of the all crime events. The *adjacency* concept is defined according to a weighted measure of distance decay w_{ij} between observations i and j (where $i \neq j$). In other words, for all crime events the mean of a variable and the deviation from the mean is calculated and compared across the distance to see if nearby location tend to have more similar values than would be expected, if there were no spatial autocorrelation. The results from the test show either positive spatial association (neighbouring segments have similar crime frequencies), or negative spatial association (segments with dissimilar values clustered together).

In this research, the Moran Correlogram was employed (Anselin; 1995) where the Moran's I values were plotted against distance. The plot shows the degree of clustering or distribution of spatial autocorrelation across the study area. Here, for every given location, concentric buffers with a gradually increasing radius were created and the Moran's I calculated for the locations situated within the corresponding buffer. The values were plotted along with 95% confidence interval obtained from Monte Carlo simulations. During the simulation, the original crime frequencies for all corresponding locations were randomly re-assigned for each iteration and the equivalent estimates of the I value derived. The final plot illustrates the observed autocorrelation value in comparison to the expected theoretical distribution assuming spatial randomness, with corresponding 2.5 and 97.5 percentiles.

Test of multicollinearity: The test determines the degree of multicolineraity between two or more independnet variables. It is defined as (Levine et.al, 2010):

$$Tol_i = 1 - R^2_{j \neq i} \qquad (8)$$

where the R^2 represents the correlation between the predictive variable j and all other variables. If the R^2 for two variables is close to 1, that is the variables are highly correlated, then their tolerance will be very low. If the variables are unrelated then the tolerance value will be high and close to 1. If a variable has a low tolerance value it should be eliminated from a given model and included into the separate regression model.

5.4.2 Results from diagnostic tests

In the following section, all 14 predictor variables will be used separately to analyse patterns observed for the three different categories of drug crime. Essentially, the regression model with the same independent variables will be analysed three times for the three different dependent variables – crime *production*, *supply* and *possession* counts, per street segments. **Table 17** lists all the variables that were used in the regression models with their corresponding descriptive summaries. Street segment length and the two sets of to-movement and through-movement permeability variables are continuous variables. The connectivity is an interval variable. The rest of the variables are binary. It should be noted that given the high range of the two sets of to-movement and through-movement variables, they were scaled by 3 decimal places. This was done in order to ease the interpretation and improve the processing time of the model. These transformations do not affect parameter estimation.

Table 17: Descriptive summary of all the variables used in the regression (n= 13,153)

		Variable	Mean	Standard deviation	Minimum value	Maximum value
1.	Dependent	Segments with production crime	0.01	0.09	0.00	3.00
2.		Segments with supply crime count	0.06	0.57	0.00	32.00
3.		Segments with possession crime count	0.44	5.01	0.00	387.00
1.	Predictive	Segment length	39.42	40.67	0.02	400.30
2.		Connectivity index	3.62	1.09	1.00	11.00
3.		High street	0.16	0.37	0.00	1.00
4.		Adjacent to high street	0.16	0.37	0.00	1.00
5.		A road	0.09	0.29	0.00	1.00
6.		B road	0.74	0.26	0.00	1.00
7.		Roundabout, road slips	0.04	0.20	0.00	1.00
8.		Private access road	0.05	0.23	0.00	1.00
9.		Local road	0.33	0.47	0.00	1.00
10.		Paths, alleys	0.38	0.48	0.00	1.00
11.		To-movement perm.(r800m)	0.15	0.05	0.02	0.36
12.		To-movement perm.(r4000m)	1.91	0.55	0.46	3.42
13.		Through-movement perm.(r1200m)	18.44	30.21	0.00	201.50
14.		Through-movement perm.(r4000m)	644.26	1640.88	0.00	13476.00

First, the frequency distribution of the dependent variable was plotted for all three types (**Figure 27**). It can be seen that, although some street segments have multiple occurrences of crime (possession cases up to 387 incidents), the overall distribution of crime counts is highly skewed with a large number of street segments having 0 crime. Most of the *crime prone* segments have 1 crime and very few segments have more than 10 incidents of drug crime. It can be suggested that the distribution of crime frequencies per street segment resembles a Poisson distribution for which the most typical value is 0. Furthermore, the test of skewness for the dependent variable was significant and highly skewed, see **Table 18**. The ratios of simple variance to mean were 6:1 and 57:1 for drug supply and possession cases, respectively, indicating that the dependent variables were over-dispersed.

Table 18: Summary of diagnostic tests for dependent variable (n = 13,153)

N	Test name & estimation parameter		Drug crime type		
			Production	*Supply*	*Possession*
1.	**Test of skewness**	g	15.00***	2.80***	56.10***
		SES	0.02	0.02	0.02
		z	705.00	1211.00	2643.00
2.	**Ratio of variation to mean**		1.20	5.60	57.30
3.	**Moran's I**		$0.000^{n.s.}$	0.002**	0.002**

*** p<0.001, ** p<0.010

The second diagnostic test for dependent variables was the test of autocorrelation. **Table 18** shows that only drug production cases were not spatially dependent. Both drug supply and possession cases have small but significant Moran's I value (I = 0.002, p<.001). The Moran correlogram with simulated 95% confidence interval estimated from Monte Carlo simulation with 100 iterations is shown as **Figure 28**. It is apparent that in comparison to a theoretical random distribution, the observed autocorrelation value of the drug supply and possession cases showed significant positive autocorrelation up to 3.5 - 4 km. Over the large scale, the autocorrelation gradually decreases. In contrast, for drug production cases there appeared not to be any autocorrelation: the observed Moran I value falls between 2.5 and 97.5 simulated percentiles.

Figure 27: Frequency distribution of drug crime cases per street segment (sample size n = 13,153 segments, logarithmic scale with base of 10)

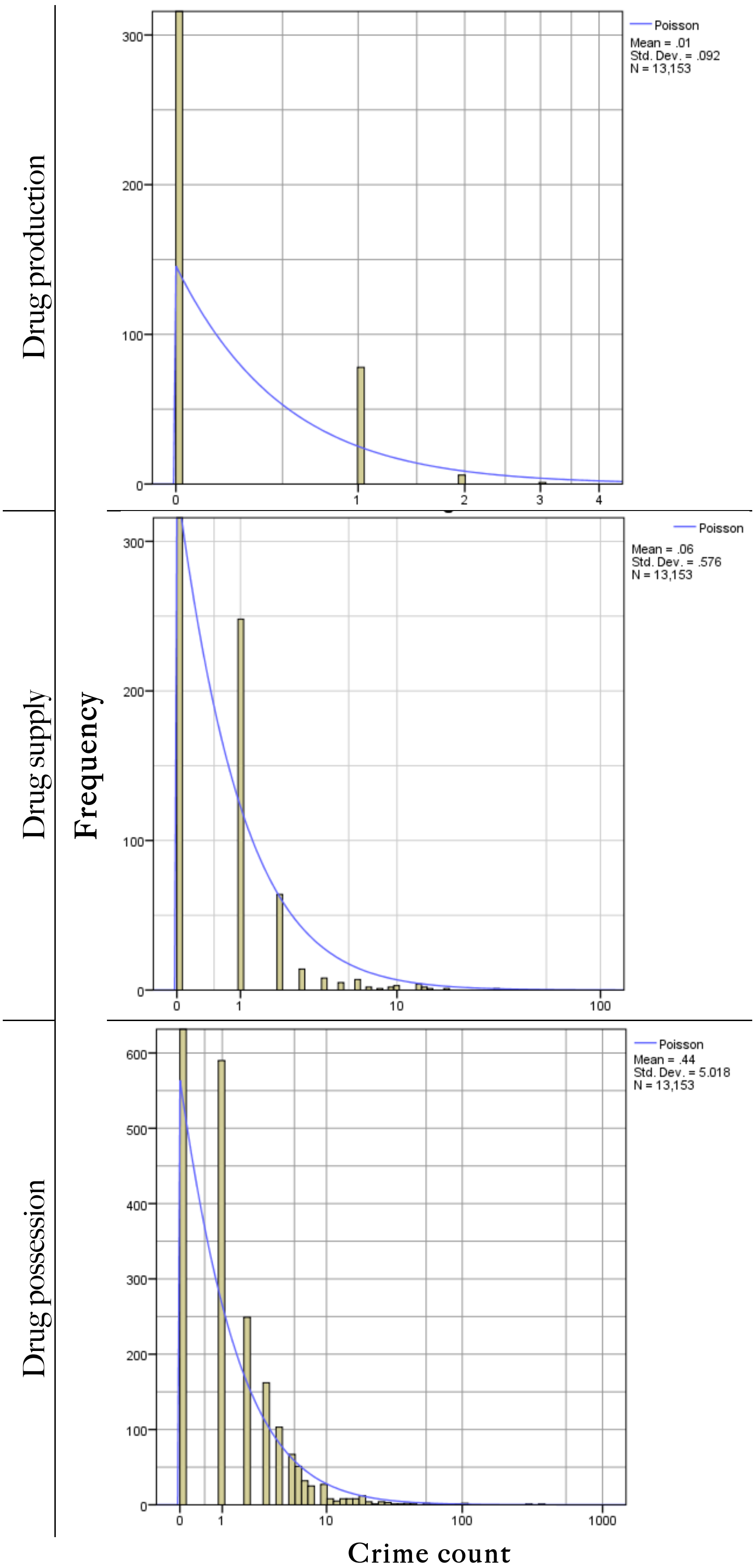
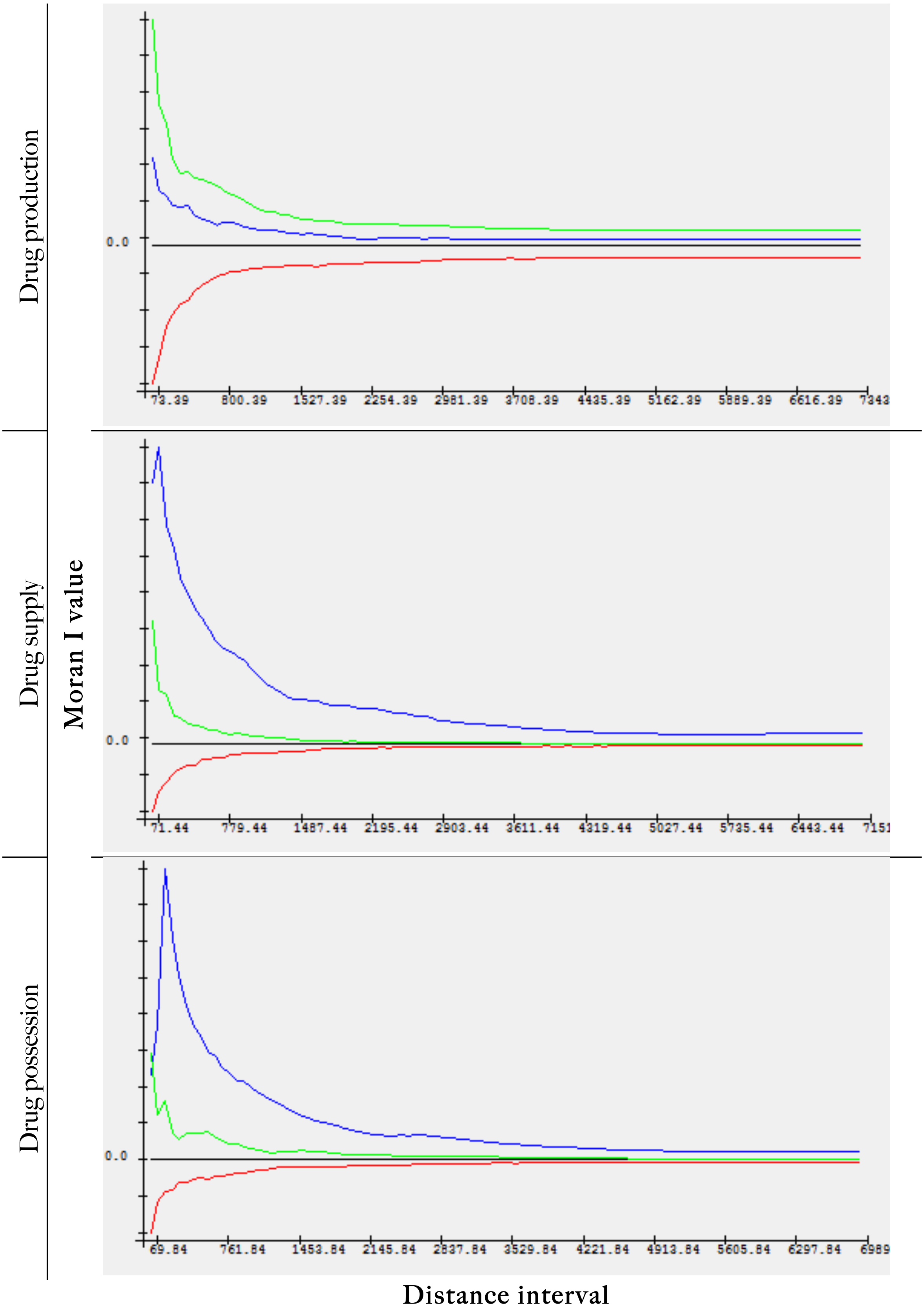


Figure 28: Moran's I value (blue) and 2.5 (red) and 97.5 (green) simulated percentiles plotted against the distance intervals, for three different drug crimes (n = 13,153 segments, 100 Monte Carlo iterations)



For the *predictor variables* a diagnostic test of multicolinearity was conducted for all 14 independent variables. **Table 19** shows the pseudo-tolerance tests and the corresponding variable selection procedure used to specify regression model(s). It can be seen that in total, 7 tests of pseudo-tolerance were performed. In the first model, all 14 variables were included and it was assumed that if there was no multicolinearity among the variables, all would be included into a single regression model. CrimeStat software automatically outputs the tolerance values for corresponding independent variables and indicates whether or not there is multicolinearity. It can be seen that the first model is definitely unreliable, since too many variables have low tolerance values, which indicates that they are highly correlated with each other. This is not surprising as the "High street" and "A road" variables overlap considerably, since most of the high streets in London are located on A roads. Likewise, the configurational value of "to-movement" calculated for local and regional scale will measure the same property of the street network at different scales of permeability (see model 3 in the **Table 19**). Thus, a rule was adopted to exclude the highly correlated variables from the models in order to reduce multicolinearity. Following this rule, in the second model, only variables with high tolerance value were analysed plus the "high street" variable. The test showed no apparent correlation between the predictor variables, thus these four were included in the first regression model, see **Table 20**. For the four configuration values that measure street segment permeability, because of the low tolerance values, it was decided to conclude four separate regression models, see **Table 19**. In the last group of predictor values, the "local road" and "path, alleys" variables appeared to be correlated, thus both of them were tested in separate models.

Table 19: Summary of pseudo-tolerance tested for independent variables

	Predictor	Pseudo-tolerance test[1]						
		1	**2**	**3**	**4**	**5**	**6**	**7**
1.	Segment Length	0.88	0.96	0.98	0.91	0.91	0.98	0.88
2.	Connectivity index	0.71	0.95	----	----	----	----	----
3.	High Street	**0.66**	0.97	----	----	----	----	----
4.	Adjacent to high street	0.82	0.98	----	----	----	----	----
5.	To-movement (r800m)	**0.23**	----	**0.25**	----	----	----	----
6.	To-movement (r4000m)	0.33	----	0.36	----	----	----	----
7.	Through-movement (r1200m)	0.24	----	0.30	----	----	----	----
8.	Through-movement (r4000m)	0.28	----	0.41	----	----	----	----
9.	A road	**0.42**	----	----	0.85	0.88	0.96	----
10.	B road	0.62	----	----	0.88	0.90	0.97	----
11.	Roundabout, road slips	0.83	----	----	0.93	0.93	0.98	----
12.	Private access road	0.92	----	----	0.91	0.92	0.98	----
13.	Local road	0.53	----	----	0.75	**0.80**	----	0.67
14.	Paths, alleys	0.55	----	----	**0.70**	----	----	**0.64**
	Result of multicolinearity	*Definite*	**No apparent**	*Definite*	*Definite*	*Possible*	**No apparent**	*Definite*

[1] Predictor with lowest tolerance value in the tested group is highlighted

Table 20 lists the final 8 models with the corresponding independent variables that will be tested in a regression model.

Table 20: The independent variables to be tested per single regression model

Model N	Independent variable(s)
1	Segment length, Connectivity index, High street, Adjacent segments to high street
2	Segment length, To-movement (r800m)
3	Segment length, To-movement (r4000m)
4	Segment length, Through-movement (r1200m)
5	Segment length, Through-movement (r4000m)
6	Segment length, A road, B road, Roundabout, road slips, Private access road
7	Segment length, Local road
8	Segment length, Paths, alleys

The next section presents the event count regression models followed by the statistical analysis.

5.4.3 Event count regression modelling

The inferential regression model uses the *predictor* (independent) variable(s) to measure the *observed* (dependent) variable and make predictions as to how the dependent variable will change if one of the independent variables changes its value, whereas others remained constant, **Equation 8**. The expected values from regression analysis are modelled according to a certain functional relationship (f) between dependent (y) and independent $(x_{1,2,\dots k})$ variables plus an error term (ε) that indicates the difference between the actual value of the dependent variable and the one that was predicted from the relationship.

$$y_i = f(x_{1i}, \dots, x_{ki}) + \varepsilon_i \tag{9}$$

The most common functional relationship used for statistical analysis is the *normal linear relationship*, **Equation 9**.

$$y_i = \beta_0 + \beta_1 x_{1i} + \cdots + \beta_k x_{ki} + \varepsilon_i \tag{10}$$

Here, the function relationship between variables is described as linear; where a one-unit change in the predictive variable (x_j) is associated with a β_j unit change in the dependent variable (y). The relative effect of the independent variable(s) on the dependent one is specified by coefficient (β). β_0 coefficient in the equation is the intercept that is added to all observations.

In order to evaluate how well the specified independent variables predict the dependent variable, an assessment of the goodness of fit of the model needs to be performed. The Maximum Likelihood Estimation (MLE) method is used to find the probability distribution of specified values that maximise the likelihood of observed data. Essentially, MLE estimates the parameters of the regression model that best fit the observed data.

Commonly the crime data will infringe the assumptions of normal regression model: the distribution is skewed, due to the fact that crime is a relatively rare event and does not occur everywhere in the city, moreover crime events tends to cluster, thus be spatially autocorrelated. So, a special non-parametric regression approach need to be adopted that accounts for the skewed property of crime counts and captures the spatial autocorrelation in error terms. Levine and colleagues (Levine et al, 2010) proposed using regression models that have Poisson distribution with a Conditional Autoregressive (CAR) term that accounts for spatial influences in the data. This model was adopted using the algorithms implemented in CrimeStat IV (Levine, 2010).

Firstly, the distribution of crime counts was modelled according to the 'law of rare events' (Cameron and Trivedi, 1998) that replicates the Poisson distribution, where the crime incident occurs across a large number of street segments, but the likelihood of it occurring at every street segment is very small. If y is the number of crimes per street segment, then the mean count of crime per segment is ƛ, thus the probability of observing y_i for the given segment is defined as:

$$\text{Prob}\ (y_i) = \frac{e^{ƛ} ƛ^{y_i}}{y_i!} \tag{11}$$

where, $e^{ƛ}$ is a natural constant equal to 2.71. The y_i follows a Poisson distribution and the ƛ parameter represents both the mean and variance of the distribution. However, Levine and colleagues (Levine et al, 2010) argue that traditional Poisson regression is not appropriate for crime data since it does not account for the degree of over-dispersion of the dependent variable, which may be much more than expected by the Poisson distribution. They suggested incorporating into a single regression model two different assumptions about the structure of crime data, where the mean is mathematically separated from the variance of the distribution. Thus, both the dependent variable and the mean follow Poisson distribution, and the variance follows a Gamma distribution. Levine and colleagues modelled this regression function as (Levine et al, 2010):

$$y_i | ƛ_i \sim Poisson\ (ƛ_i) \tag{12}$$

where ƛ is the mean defined as:

$$ƛ_i = \exp\ (x_i^T \beta + \ \varepsilon_i) \tag{13}$$

where the exponential function $exp()$ models the independent variable $(x_{1,2,\ldots i})$ with corresponding coefficients (β) and intercept, plus the $exp(\varepsilon_i)$ error term, which reflects the Gamma distribution with the mean of 1 and a variance modelled as a ratio of $\frac{1}{\Psi}$, where Ψ is negative and is the amount of dispersion (Levine et.al 2010).

Secondly, in order to account for spatial autocorrelation in the data, Levin and colleagues (2010) proposed incorporating into the Poisson-Gamma regression model a spatial random effect Phi (ϕ_i) for every corresponding observation, thus the new mean of the model (Equation 7) is expressed as:

$$\lambda_i = \exp\,(x_i^T\beta + \varepsilon_i + \phi_i) \tag{14}$$

where (ϕ_i) is a function of three parameters that are additive:

$$\phi_i|\Phi_{-i} \sim N\left(\rho\sum_{j\neq i}^{n}(w_{ij}/w_{i+})\phi_j, \sigma_{\phi}^2/w_{i+}\right) \tag{14}$$

a global parameter that is applied to all street segments and denoted as Rho (ρ), the local parameter, applied to the sub-sets of street segments and denoted as Tauphi (τ_{ϕ}) and the neighbouring parameter Alpha (α) with spatial weight function applied to localized adjacent street segments up to a certain distance away.

In this research the local autocorrelation is estimated using Conditional Autoregressive (CAR) format and is defined as (Levine et.al 2010):

$$E(y_i|y_{j\neq i}) = \mu_i + \rho\sum_{j\neq i} w_{ij}\,(y_j - \mu_j) \tag{15}$$

where μ_i is the expected drug crime for segment i, w_{ij} is a spatial weight between the segment, i, and all other segments, j, and ρ is a spatial autocorrelation parameter (Levine et.al 2010).

In order to identify the spatial weights between two neighbouring segments, in this research 'restricted negative exponential distance decay' function is used (Levine et.al; 2010):

$$w_{ij} = Ke^{-\alpha d_{ij}} \tag{15}$$

where d_{ij} is the distance between two street segments. A spatial weight of 1 is applied to street segments if they are within the search distance K (that is $d_{ij} \leq K$) and the weight becomes 0 if the segments are further apart ($d_{ij} > K$). In the CAR model the spatial weight is applied to the calculated difference between observed and predicted values at all street segment locations.

To summarise the Poisson-Gamma-Car model is a spatial regression model with three mathematical components – Poisson mean, Gamma dispersion and spatial autocorrelation component in CAR format.

As mentioned above, the Maximum Likelihood Estimation (MLE) method is used to estimate the parameters in the Poisson-Gamma regression model. For the more complicated Poisson-Gamma-Car model, Markov Chain Monte Carlo (MCMC) estimation method is used (Levin et al, 2010), that utilises a Bayesian approach. Here prior coefficient estimates are assigned to the model. The Markov chain generates a sequence of samples. Here conditional probability is used, when the prior probabilities of a sample are systematically updated with regards to the previous sample only. The final values for coefficients and corresponding statistics are the average summary over all samples drawn during the simulation. It is based on $M - L$ samples, where from all M number of iterations, the L number of samples where rejected as an interval when the MCMC algorithm was reaching equilibrium state.

Additionally, both Poisson-Gamma regression models produce five likelihood statistics that characterise how well the model predicts the observed data:

- Log likelihood;
- Aikaike Information Criterion (AIC);
- Bayes Information Criterion or Schwartz Criterion (BIC/SC);
- Deviance statistics;
- Pearson chi-square statistics.

The log likelihood function is the joint probability density of all observations from the data. With the Poisson model it is always negative, but the larger the value (closer to 1) the better. The log likelihood is defined as:

$$lnL = \sum_{i=1}^{N}[-\lambda_i + y_i \ln(\lambda_i) - lny_i!] \tag{16}$$

where y_i is the number of crime per street segment and λ_i is the mean for the segment i. The log likelihood automatically increases, when more predictive variables are added to the model. Both AIC and BIC/SC penalise the number of variables added, therefore the model that has the lowest information criterion value is considered to be the best. AIC is defined as:

$$AIC = -2L + 2(K + 1) \tag{17}$$

where K is the number of predictive variables. And BIC/SC is defined as:

$$BIC/SC = -2L + [(K + 1)\ln(N)] \tag{18}$$

The deviance statistic assesses whether the Poisson model is applicable for the given structure of the data. It is defined as:

$$Dev = 2\,(L_F - L_M) = 2\sum_{i=1}^{N}\left[y_i ln\left(\frac{y_i}{\widehat{\lambda_i}}\right) - y_i - \widehat{\lambda_i}\right] \tag{19}$$

The deviance is calculated by comparing the L_F log likelihood of the perfect fit model to the L_M log likelihood of the model being tested. If the value of deviance is greater than $N - (K + 1)$, where N is the sample size and K is the number of variables, then the model is considered to be over-dispersed.

The Pearson chi-square statistics also assess the degree of over-dispersion. It is defined as:

$$X^2 = \sum_{i=1}^{N}\frac{(y_i - \widehat{\lambda_i})^2}{\widehat{\lambda_i}} \tag{20}$$

And if $\frac{X^2}{(N-K-1)} > 1$ then there is an over-dispersion in the data.

The Poisson-Gamma regression model also estimates the error in the model, mainly how good the defined model fits the observed data. The smaller the value for the Mean Absolute Deviance (MAD) and Mean Squared Predicted Error (MSPE), the better is the model fit.

To summarise, the final Poisson-Gamma regression model shows the estimated coefficients for corresponding predictive variables coupled with five likelihood statistics and two model error estimates all assessing the fit of the model.

5.5 Results

5.5.1 Regression modelling drug production crime

Based on the diagnostic results, suitable regression models were chosen for the corresponding drug crime types, see **Table 21**. Given that the dependent variable, i.e. the crime count per street segment has non-normal distribution, the c*ount regression model* was used. Table 4 summarises the regression models selected depending on the statistical structure of the dependent variable. Since the drug production cases appear not to have spatial autocorrelation, a Poisson-Gamma regression model with Maximum Likelihood Estimation method was employed. However, given that there was significant autocorrelation for drug supply and possession cases, the same Poisson-Gamma regression model was selected, but with the spatial autocorrelation component, estimated using a Markov Chain Monte Carlo (MCMC) method that is implemented in Crime Stat IV.

Table 21: The regression model with estimation method selected for 3 different dependent variables with street samples corresponding to drug *production*, *supply* and *possession* crime count

Dependent variable	Moran's I	Regression model to be used	Estimation method
Production	Not significant	Skewed Poisson-Gamma	Maximum Likelihood (MLE)
Supply	0.002**	Skewed Poisson-Gamma CAR	Markov Chain Monte Carlo (MCMC)
Possession	0.002**	Skewed Poisson-Gamma CAR	Markov Chain Monte Carlo (MCMC)

First, the relationship between street network attributes and incidents of drug production crime was statistically tested. **Table 22** summarises 9 separate models of the Poisson-Gamma regression with MLE method where the dependent variable is *drug production* incidents and the unit of analysis is the street segment. For the purpose of illustration, the first model includes all 14 independent variables. The other 8 models follow the order described in Table 18. The first part of Table 22 illustrates five likelihood statistics and two model error estimates that assess the fit of the model. The second part of the table includes estimated coefficients for every predictor variable plus the intercept.

[1] CAR stands for conditional autoregressive

Table 22: Parameter estimation for 9 separate models of Poisson-Gamma regression computed using the **MLE** method, the dependent variable is ***drug production*** incidents and the unit of analysis is the *street segment* (sample size n = 13,153 segments)

Summary of goodness of fit statistic	Model 1	2	3	4	5	6	7	8	9
Log likelihood	-494.6	-500.0	-503.5	-503.6	-502.6	-503.2	-503.0	-502.7	-501.9
AIC	1019.2	1012.1	1015.0	1015.3	1013.3	1014.5	1020.0	1013.4	1011.8
BIC/SC	1131.5	1057.0	1045.0	1045.2	1043.3	1044.5	1072.4	1043.3	1041.7
Deviance	472.0***	459.3***	452.9***	453.2***	456.0***	451.6***	457.7***	459.2***	465.3***
Pearson Chi-Square	11861.4	10758.4	10483.3	10528.1	10586.7	10456.0	10638.1	10989.8	11037.3
Model error estimates									
Mean absolute deviation	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Mean squared predicted error	0.05	0.40	0.70	0.72	0.58	0.90	0.47	0.32	0.24
Individual predictors	**Coefficients**								
Intercept	-5.31***	-5.50***	-6.13***	-5.98***	-6.08***	-6.02***	-5.99***	-6.09	-5.76***
Segment length	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***
Connectivity index	-0.21*	-0.17 n.s.	----	----	----	----	----	----	----
High street	1.07*	0.99*	----	----	----	----	----	----	----
Adjacent to high street	0.44 n.s	0.36 n.s	----	----	----	----	----	----	----
To-movement (r800m)	0.92 n.s	----	0.95 n.s	----	----	----	----	----	----
To-movement (r4000m)	-0.37 n.s	----	----	-0.00 n.s	----	----	----	----	----
Through-movement (r1200m)	0.00 n.s	----	----	----	-0.00 n.s	----	----	----	----
Through-movement (r4000m)	-0.00 n.s	----	----	----	----	-0.00 n.s	----	----	----
A road	-0.19 n.s	----	----	----	----	----	-0.12 n.s	----	----
B road	0.04 n.s	----	----	----	----	----	-0.03 n.s	----	----
Roundabout, road slips	0.20 n.s	----	----	----	----	----	0.02 n.s	----	----
Private access road	0.84 n.s	----	----	----	----	----	0.45 n.s	----	----
Local road	0.67*	----	----	----	----	----	----	0.32 n.s	----
Paths, alleys	-0.67*	----	----	----	----	----	----	----	-0.53*

*** p<0.001, * p<0.050

Initially, the fit of all 9 models was compared. The largest log likelihood value, i.e. closest to 1 was obtained for model N1 followed by models N2 and N9. The lowest information criterion value, i.e. AIC and BIC was observed for model N9 followed by N2, N5 and N8. It should be noted that, since the regression model represents the approximate model of the real world, both AIC and BIC indicate how much information was lost, thus which regression model best represents the reality given set of parameters. That is, the small AIC and BIC value shows that there was a small lost of information and the model is closest to the real model.

Although, both AIC and BIC penalise when more variables are added to the model, still the model N2 performance is equally good as models that have only one explorative variable, such as models N9 or N5. The deviance value estimates whether or not the model is over dispersed. Overall, it should be smaller than the sample size minus the number of independent variables used and plus 1. Among all those tested models, model N1 has the highest number of independent variables. Given the sample size of 13,153, a value can be computed and compared to the deviance value.

$$13153 - (14 + 1) = 13138$$

None of the deviance values mentioned in the Table 6 were greater than 13138, therefore there is no over dispersion in the models. The Pearson chi-square also measures over dispersion in the model. If it is smaller than the X^2 value divided by the sample size minus the number of independent variables used and minus 1, then there is no over dispersion detected in the model. The value was calculated for model N1. It can be seen that the derived value is smaller than 1, thus the model fit is acceptable. The model error estimates are quite small for all 9 models indicating a good fit.

$$\frac{11861.46}{(13153 - 14 - 1)} = 0.90$$

In terms of the individual coefficients, 95% of confidence intervals were adopted for hypothesis testing (i.e. p<.05). It was already established that the inclusion of all variables in a single model can produce unreliable results; since there is a high degree of multicolinearity between the variables (see **Table 19** test 3, page 212). Model N1 illustrates the problem explicitly. For example it is known that "local road" and “paths, alleys” variables are correlated. In the model they both are significant but with the opposite signs. In comparison to models N8 and N9 where both variables were tested separately, only the “paths, alleys” had a significant negative association with the drug production locations. Thus, model N1 provided unreliable representation of the relationship between drug crime and the parameters of street network and should be ignored. From the 8 models it can be seen that after accounting for the variation in the segment length, the street segments that are a part of the high streets are positively and significantly associated with drug crime. In model N2 the intercept is -5.50, which indicates that on average every street segment has -5.50 drug production cases with the added contribution of 0.99 for every high street and 0.02 for every increase in the segment length. Thus, no evidence was found in favour of hypothesis N4 if anything it was the reverse. The implications of these results will be considered in the subsequent ***Discussion*** part. The remaining 11 independent variables were not associated with drug production crime.

5.5.2 Regression model of drug supply crime

Next, the *drug supply* incidents for the sample of 13,153 street segments were analysed. Although, it was established that there is significant autocorrelation in this dependent variable (see Table 18), for illustration purposes the model was first analysed using Poisson-Gamma regression model estimated with Maximum Likelihood (MLE) method and later corrected using Poisson-Gamma CAR regression model with the MCMC estimation method. The results of the former analysis are presented in the **Table 23** and the latter in **Table 25.**

For the drug supply incidents, **Table 23** indicates that the largest log likelihood values observed were for model N1 followed by models N2 and N4. These models also have the lowest information of all models tested. In all models, the deviance value is smaller than 13,138, thus the Poisson model is applicable for the given data structure. However, the Pearson chi-square value appeared to be larger than 1 for all nine models (for example, model N1 has a value of 1.3 and model N2 is 1.6). Thus, there is over dispersion in the model. Moreover, the estimates for the mean squared predicted errors are considerably larger than the estimates for the mean absolute deviation in all nine models. This indicates that the model fit is not as good as for drug production cases.

Table 23: Parameter estimation for 9 separate models of Poisson-Gamma regression computed using the **MLE** method, the dependent variable is ***drug supply*** incidents and the unit of analysis is the *street segment* (sample size n = 13,153 segments)

Summary of goodness of fit statistic	Model								
	1	2	3	4	5	6	7	8	9
Log likelihood	-1902.6	-1947.0	-1967.2	-1954.8	-1971.3	-1973.4	-1958.5	-1970.6	-1966.6
AIC	3835.2	3906.0	3942.5	3917.6	3950.6	3954.8	3931.0	3949.3	3941.3
BIC/SC	3947.4	3950.9	3972.4	3947.6	3980.6	3984.8	3983.4	3979.2	3971.2
Deviance	1249.6***	1231.6***	1210.0***	1220.1***	1202.0***	1198.3***	1204.1***	1204.3***	1209.5***
Pearson Chi-Square	16976.5	21110.6	17836.1	17624.4	17958.5	18158.6	16502.1	19779.3	18426.0
Model error estimates									
Mean absolute deviation	0.18	0.31	0.44	0.37	0.53	0.60	0.47	0.43	0.31
Mean squared predicted error	4.35	40.27	106.96	66.81	199.74	276.58	149.66	98.17	27.12
Individual predictors	**Coefficients**								
Intercept	-5.56***	-4.25***	-5.23***	-6.11***	-4.70***	-4.63***	-4.62***	-4.71***	-4.35***
Segment length	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***
Connectivity index	-0.28***	-0.16*	----	----	----	----	----	----	----
High street	1.28***	1.21***	----	----	----	----	----	----	----
Adjacent to high street	0.69***	0.96***	----	----	----	----	----	----	----
To-movement (r800m)	-1.12 n.s	----	4.15***	----	----	----	----	----	----
To-movement (r4000m)	0.84***	----	----	0.77***	----	----	----	----	----
Through-movement (r1200m)	0.00*	----	----	----	0.00*	----	----	----	----
Through-movement (r4000m)	-0.00 n.s	----	----	----	----	-0.00 n.s	----	----	----
A road	-0.89*	----	----	----	----	----	-0.50*	----	----
B road	0.34 n.s	----	----	----	----	----	0.58**	----	----
Roundabout, road slips	-1.80*	----	----	----	----	----	0.54*	----	----
Private access road	1.02***	----	----	----	----	----	-1.91**	----	----
Local road	0.62***	----	----	----	----	----	----	0.32*	----
Paths, alleys	0.62***	----	----	----	----	----	----	----	-0.58***

*** p<0.001, ** p<0.010, * p<0.050

In the case of individual predictor variables it can be seen that out of the 14 independent variables, 13 were significant at the .05 confidence level. A positive association with drug supply observed for 9 variables, the rest had a negative relationship. Overall, the results suggest a significant effect of the level of permeability on drug dealing sites, as predicted by hypothesis N1. It appears that drug dealers are more likely to target locations that are permeable for movement. However, the scale of permeability is somewhat ambiguous. At one end of the spectrum, those segments that were categorised as private access roads and that had restricted public access were negatively associated with drug supply cases (model N7). At the other end of the spectrum, A roads that facilitate regional movement were also negatively associated with drug crime. For this model, it looks as if the streets that are of local importance and have local scale of permeability (i.e. B roads, local roads) are more associated with drug dealing places than are streets that accommodate regional flows of movement. However, when permeability is examined in terms of street layout configuration, both scales of movement, i.e. the local within 10 minute walk and the regional within 20 minute of driving are positively associated with the location of drug supply sites. Also, there was a significant association between street segments that have a chain of retail facilities on them and the adjacent street segments and the location of drug supply incidents.

However, it was mentioned earlier that this is an incomplete model since it does not account for spatial autocorrelation. Therefore, the same dependent variable with 14 independent variables was examined using *Poisson- Gamma regression model with a Conditional Autoregressive* (CAR) term that accounts for spatial effect. Prior to the regression analysis, the model was calibrated. To do so, three sets of initial parameters were defined for the model:

1. The number of simulations, including the number of iterations to be discarded as a 'burn in' period (see below), block sampling threshold with average block size and number of samples to be drawn (see below),
2. Initial values for the beta (β) coefficents including the intercept, in order to start running the simulation model,

3. Estimation of the spatial structure of autocorrelation and identification of the alpha (α) weight and the distance decay function accordingly.

First, the number of simulations should be sufficient in order to produce reliable results. All the results from the regression models estimated using the MCMC method were based on 100,000 iterations with the first 10,000 being discarded as a 'burn in' period to allow the model achieved an equilibrium state. That is the results are based on the remaining 90,000 iterations. Then the model convergence statistics was checked to examine whether the algorithm converged properly. Levine and colleagues (2010) recommend verifying the number of iterations based on two statistics:

1) The ratio of Monte Carlo simulation error by the standard deviation of the parameters ($\frac{\text{MC Error}}{\text{Standard Deviation}}$)
2) Gelman-Rubin (G-R) statistics, that compares the variation of a parameter within a sample approximates to the total variation across the sample.

If the first test is less than 1.05 and second test is below 1.20 then the model and corresponding estimations are considered reliable.

In order to reduce the calculation time that will take to run a single regression model, a block of samples of street segments were selected to run the regression. Scholars recommend drawing between 20 to 30 samples for a single regression model. In this research, 25 samples were drawn. For every sample, 2000 street segments were randomly selected from the case study area (13,153 segments).

Second, the intercept and initial β coefficient values for the MCMC model were obtained by conducting a Poission regression using the Maximum Likelihood Estimation method. For example, in order to run the **model 2** from the **Table 23** as a new Poisson- Gamma CAR model, the β coefficients from the intial model should be incorporated into a calibration of the new model, i.e.:

$$Y_i = e^{4.25+0.02X_{1i}-0.16X_{2i}+1.28X_{3i}+0.69X_{4i}} \qquad (21)$$

That is the following numbers were used for the calibration of Poisson-Gamma CAR model:

4.25, 0.02, -0.16, 1.28, 0.69

Third, the autocorrelation term *(ϕ)* is defined based as a function of three parameters: Rho *(ρ)*, Tauphi (τ_{ϕ}) and Alpha (α*).* The first two are the global and local parameters applied to all street segments and were pre-defined as 0.5 and 1 respectively. The neighbouring parameter α with corresponding distance decay function was derived based on the Moran's correlogram for drug supply incidents (see **Figure 28,** page 210). From Figure 28 it can be seen that the slope of the autocorrelation value decreases gradually reaching up to 2.5 kilometers. Thus, a higher weight for adjacent segments was assigned and it was assumed that with increasing distance between observations the weight would decrease. After some specified distance no weight will be assigned to the obseravations, since they are not spatially correlated. In CrimeStat (Levine et al. 2010) the alpha *(α)* value for a shallow distance decay is defined as:

$$\alpha = \frac{\ln{(0.9)}}{NND} \tag{22}$$

where NND is the distance between nearest neighbours. For the drug supply cases, the estimated α was equal to -8.692668. Thus, a weight of 1 was applied for a segment with itself and -8.692668 for the neighbouring segments up to the specified search distance. Based on the Moran's correlogram, the search distance was chosen up to 2 miles (3.2 km). The weight was 0 for segments that were more than 2 miles apart.

Table 24 shows the output from CrimeStat software for model N1 from **Table 25**. It can be seen that the model converged (MC error/std < 1.05 and G-R < 1.20). The remaining 7 models from Table 25 were checked in the same manner.

Table 24: The example of output from CrimeStat software of Poisson Gamma regression with MCMC estimation method for drug supply model

	Mean	Std	t-value	p-value	Adj_Std	Adj. t-value	Adj. p-value	MC error	MC error/ std	G-R stat
Intercept:	-4.677864	0.756686	-6.182038	0.001	0.293970	-15.912744	0.001	0.029788	0.039367	1.057760
Segment_Le:	0.028161	0.005397	5.217678	0.001	0.002097	13.430453	0.001	0.000124	0.023001	1.009871
HighStre_1:	0.937133	0.889916	1.053058	n.s.	0.345729	2.710602	0.010	0.013628	0.015314	1.013219
OneStepHiS:	1.173818	0.438446	2.677225	0.010	0.170334	6.891255	0.001	0.006754	0.015403	1.009588
Connectivi:	-0.217332	0.181169	-1.199607	n.s.	0.070384	-3.087823	0.010	0.006117	0.033767	1.015483
Spatial autocorrelation										
(Phi):	-0.002938	0.021609	-0.135979	n.s.	0.008395	-0.350015	n.s.	0.000183	0.008448	1.002945
Global component										
(Rho):	0.105936	0.086944	1.218449	n.s.	0.033777	3.136322	0.010	0.000448	0.005154	1.000127
Local component										
(Tauphi):	8.220553	19.946756	0.412125	n.s.	7.749235	1.060821	n.s.	1.113048	0.045801	1.151168
Neighborhood component										
(Alpha: defined)		-8.692668 Miles								
Search distance		2.000000 Miles								

The average estimations from all 25 samples drawn are presented in **Table 25**. The largest log likelihood value and the smallest information criterion has the model N1 followed by N5. All the deviance values are smaller than 13,148 indicating that the Poisson model is applicable for the given data structure. However, the Pearson chi-square value appeared to be larger than 1 for all eight models (for example, model N1 = 3.9 and model N2 = 3) suggesting over dispersion that was not accounted for by the model. The spatial autocorrelation term is not significant showing that the model has successfully accounted for the clustering of the dependent variable.

These more refined models show (see **Table 25**) that indeed there is a significant association between the level of movement permeability and drug dealing. That is, the results suggest that drug dealers target the locations that have high movement flow potential. After accounting for segment length, for every increase in spatial permeability for intra-city scale movement, there is an increase of 0.74 of drug dealing crime (model N3). Moreover, it is clearly evident that for every high street being present in the adjacent vicinity from the given street segment, it increases the likelihood of drug crime on adjacent streets by 1.17 (model N1). Thus, there is evidence in favour of hypothesis N2. It should be noted that some of the earlier findings from **Table 23** are no longer significant.

Table 25: Parameter estimates for 8 separate models of Poisson-Gamma-CAR regression computed using the **MCMC** method, which incorporated spatial autocorrelation estimation, the dependent variable is ***drug supply*** incidents and the unit of analysis is the *street segment* (sample size n = 13,153 segments)

Summary of goodness of fit statistic	**Model**							
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Log likelihood	-2005.4	-2012.2	-2020.7	-2084.5	-2008.4	-2287.1	-2049.7	-2026.2
AIC	4025.0	4034.5	4051.5	4179.0	4026.8	4590.2	4109.5	4062.5
BIC/SC	4077.3	4071.9	4088.9	4216.5	4064.2	4650.1	4146.9	4100.0
Deviance	1634.7***	1581.8***	1659.3***	1881.6***	1477.5***	2094.5***	1675.1***	1639.2***
Pearson Chi-Square	11348.4	10541.0	11721.3	11394.6	11138.7	11972.0	10393.8	11715.9
Model error estimates								
Mean absolute deviation	0.22	0.31	0.20	0.26	0.39	0.37	0.14	0.18
Mean squared predicted error	21.61	48.81	13.90	35.84	99.94	109.98	2.75	5.35
Individual predictors	**Coefficients**							
Intercept	-4.68***	-5.89***	-6.58***	-5.33***	-5.03***	-4.96***	-5.27***	-4.80***
Segment length	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***
Connectivity index	-0.21 $^{n.s}$	----	----	----	----	----		----
High street	0.93 $^{n.s}$	----	----	----	----	----	----	----
Adjacent to high street	1.17***	----	----	----	----	----	----	----
To-movement (r800m)	----	5.34 $^{n.s}$	----	----	----	----	----	----
To-movement (r4000m)	----	----	0.74*	----	----	----	----	----
Through-movement (r1200m)	----	----	----	0.00 $^{n.s}$	----	----	----	----
Through-movement (r4000m)	----	----	----	----	-0.00 $^{n.s}$	----	----	----
A road	----	----	----	----	----	-0.84 $^{n.s}$	----	----
B road	----	----	----	----	----	0.29 $^{n.s}$	----	----
Roundabout, road slips	----	----	----	----	----	- 61.68*		----
Private access road	----	----	----	----	----	0.01 $^{n.s}$	----	----
Local road	----	----	----	----	----	----	0.60 $^{n.s}$	----
Paths, alleys	----	----	----	----	----	----	----	-0.77 $^{n.s}$
Spatial autocorrelation (Phi)	-0.00 $^{n.s}$	-0. 00 $^{n.s}$	-0. 00 $^{n.s}$	-0.00 $^{n.s}$	-0.00 $^{n.s}$	-0.00 $^{n.s}$	-0.00 $^{n.s}$	-0.00 $^{n.s}$

*** p<0.001, * p<0.050

5.5.3 Regression modelling drug possession crime

For incidents of drug possession, a Poisson-Gamma regression computed using MLE was calculated (see **Table 26**). The largest log likelihood and smallest information criterion was for model N1 followed by model N2. In all models, the deviance value is considerably smaller than 13,138, indicating that the Poisson model is applicable for the given data structure. However, similar to drug supply cases, the Pearson chi-square value of drug possession cases is larger than 1 for all nine models (for example, model N1 is 5 and model N2 is 4.6). Thus, there is over dispersion in the model. Moreover, the model error estimates are very large (sometimes reaching up to 10 digits), indicating that the model fit is not as good as for the drug production and supply cases.

Similar to the drug supply model, the coefficients for 12 of the 14 variables were statistically significant at the .05 confidence level. A positive association with drug possession incidents was observed for 8 variables, the rest had a negative relationship. The results suggest a significant association with the level of street permeability (hypothesis N7). It appears that drug dealers are more likely to target locations that are permeable for movement at both the local and regional scales. Similar to drug supply crime, A roads, roundabouts and urban paths were negatively associated with the location of incidents. In contrast, B roads and local roads were positively associated with on drug possession indicating that roads of local importance were targeted more for drug possession. Both the high street segments and adjacent streets were significantly associated with the location of drug possession crime.

Table 26: Parameter estimation for 9 separate models of Poisson-Gamma regression computed using the **MLE** method, the dependent variable is ***drug possession*** incidents and the unit of analysis is the *street segment* (sample size n = 13,153 segments)

Summary of goodness of fit statistic	**Model 1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Log likelihood	-6757.9	-6850.2	-6931.7	-6901.3	-6945.5	-6944.3	-6925.3	-6941.4	-6943.6
AIC	13545.8	13712.4	13871.4	13810.7	13899.1	13896.7	13864.7	13890.9	13895.3
BIC/SC	13658.0	13757.3	13901.4	13840.7	13929.0	13926.6	13917.1	13920.8	13925.2
Deviance	3623.9***	3600.5***	3573.6***	3592.1***	3563.9***	3564.4***	3568.9***	3564.1***	3565.3***
Pearson Chi-Square	66124.7	60984.3	96113.2	95866.1	95294.0	95889.8	90230.9	96534.9	102254.8
Model error estimates									
Mean absolute deviation	76.11	434.48	747.94	478.14	>1000.00	>1000.00	720.22	909.93	960.70
Mean squared predicted error	>1000.00	>1000.00	>1000.00	>1000.00	>1000.00	>1000.00	>1000.00	>1000.00	>1000.00
Individual predictors	**Coefficients**								
Intercept	-2.86***	-1.82***	-3.15***	-3.86***	-2.65***	-2.64***	-2.58***	-2.69***	-2.51***
Segment length	0.03***	0.03***	0.03***	0.03***	0.03***	0.03***	0.03***	0.03***	0.03***
Connectivity index	-0.40***	-0.31***	----	----	----	----	----	----	----
High street	0.71***	1.13***	----	----	----	----	----	----	----
Adjacent to high street	0.59***	1.02***	----	----	----	----	----	----	----
To-movement (r800m)	1.37 n.s	----	3.71***	----	----	----	----	----	----
To-movement (r4000m)	0.62***	----	----	0.65***	----	----	----	----	----
Through-movement (r1200m)	-0.00*	----	----	----	0.00 n.s	----	----	----	----
Through-movement (r4000m)	0.00***	----	----	----	----	0.00*	----	----	----
A road	-1.48***	----	----	----	----	----	-0.52***	----	----
B road	0.45*	----	----	----	----	----	0.39*	----	----
Roundabout, road slips	-1.49***	----	----	----	----	----	-0.95***	----	----
Private access road	0.41*	----	----	----	----	----	0.11 n.s	----	----
Local road	0.45***	----	----	----	----	----	----	0.25*	----
Paths, alleys	-0.45***	----	----	----	----	----	----	----	-0.20*

*** p<0.001, * p<0.050

The models were further examined using Poisson- Gamma regression model with CAR term to account for spatial autocorrelation. Prior to the regression analysis the model was again calibrated. The number of simulations, the iteration parameters and initial coefficient values were chosen in the same way as before. The alpha parameter was chosen based on the Moran's correlogram graph (see **Figure 28,** page 210) and **Equation 22** (page 228). The distance decay function was set as up to 2.5 miles (4 km) and α was equal to -8.654320. Thus, a weight of 1 was applied for a segment with itself and -8.654320 for the neighbouring segments up to the specified search distance of 2.5 miles. A 0 weight was applied on the segments that were more than 2.5 miles away from each other. The regression model properly converged (MC error/std < 1.05 and G-R < 1.20, see **Table 27**). All models from the **Table 28** were checked in the same manner.

Table 27: The example of output from CrimeStat software of Poisson Gamma regression with MCMC estimation method for drug possession model

	Mean	Std	t-value	p-value	Adj_Std	Adj. t-value	Adj. p-value	MC error	MC error/ std	G-R stat
Intercept:	-3.627987	0.269176	-13.478097	0.001	0.105070	-34.529301	0.001	0.009128	0.033911	1.011728
Segment_Le:	0.032764	0.003379	9.695492	0.001	0.001319	24.838712	0.001	0.000057	0.016883	1.001712
Choic_4000:	0.000049	0.000063	0.767472	n.s.	0.000025	1.966173	0.050	6.1986e-007	0.009768	1.000608
Spatial autocorrelation										
(Phi):	-0.011380	0.031697	-0.359014	n.s.	0.012372	-0.919751	n.s.	0.000239	0.007547	1.000460
Global component										
(Rho):	0.124801	0.097321	1.282370	n.s.	0.037988	3.285282	0.010	0.000682	0.007009	1.000298
Local component										
(Tauphi):	0.041313	0.018172	2.273487	0.050	0.007093	5.824406	0.001	0.000885	0.048722	1.027099
Neighborhood component										
(Alpha: defined)		-8.654320 Miles								
Search distance		2.500000 Miles								

The Poisson-Gamma MCMC model (see **Table 28**) showed that drug possession is also significantly associated with permeability for to-movement at both scales of movement. Also a significant positive effect was found with segments that were coded as local roads. The urban pathways and alleys were negatively associated with drug possession cases. The connectivity index was also negatively associated with drug possession crime.

Table 28: Parameter estimation for 8 separate models of Poisson-Gamma-CAR regression computed using the **MCMC estimation** method, which incorporated spatial autocorrelation estimation, the dependent variable is ***drug possession*** incidents and the unit of analysis is the *street segment* (sample size n = 13,153 segments)

Summary of goodness of fit statistic	1	2	3	4	5	6	7	8
Log likelihood	-7726.8	-7657.3	-7726.8	-7620.7	-7748.6	-8047.4	-8247.2	-8082.7
AIC	15467.7	15324.6	15463.6	15251.4	15507.2	16110.9	16504.5	16175.5
BIC/SC	15520.1	15362.1	15501.0	15288.8	15544.7	16170.8	16541.9	16212.9
Deviance	6971.5***	6471.7***	6869.5***	6402.4***	6745.6***	7544.9***	8029.1***	7645.5***
Pearson Chi-Square	13121.3	11702.4	11424.6	16039.9	12227.6	13698.5	11541.9	12918.9
Model error estimates								
Mean absolute deviation	4.05	38.64	34.95	56.41	68.23	68.09	39.36	57.45
Mean squared predicted error	138.00	296.00	274.80	696.32	734.02	553.00	373.23	543.32
Individual predictors	**Coefficients**							
Intercept	-6.19***	-4.21***	-4.93***	-3.60***	-3.62***	-3.70	-4.00***	-3.31***
Segment length	0.02	0.03***	0.03***	0.03***	0.03***	0.03***	0.03***	0.03***
Connectivity index	-0.24*	----	----	----	----	----	----	----
High street	1.05***	----	----	----	----	----	----	----
Adjacent to high street	0.87*	----	----	----	----	----	----	----
To-movement (r800m)	----	4.24*	----	----	----	----	----	----
To-movement (r4000m)	----	----	0.70***	----	----	----	----	----
Through-movement (r1200m)	----	----	----	$0.00^{n.s}$	----	----	----	----
Through-movement (r4000m)	----	----	----	----	$0.00^{n.s}$	----	----	----
A road	----	----	----	----	----	$-0.68^{n.s}$	----	----
B road	----	----	----	----	----	$0.41^{n.s}$	----	----
Roundabout, road slips	----	----	----	----	----	$0.29^{n.s}$	----	----
Private access road	----	----	----	----	----	$-3.39^{n.s}$	----	----
Local road	----	----	----	----	----	----	0.75*	----
Paths, alleys	----	----	----	----	----	----	----	-0.77*
Spatial autocorrelation (Phi)	$-0.00^{n.s}$	$-0.00^{n.s}$	$-0.00^{n.s}$	$-0.00^{n.s}$	$-0.00^{n.s}$	$-0.00^{n.s}$	$-0.00^{n.s}$	$-0.00^{n.s}$

*** p<0.001, * p<0.050

5.6 Discussion

The aim of Chapter 5 was to test hypotheses regarding the geographical distribution of drug crime in the city, mainly to what extent drug offender decision-making might be influenced by the urban street layout. Studies of drug crime propose that urban characteristics influence drug trading locational choices and that offenders select locations that will maximise their utility. However, these do not examine explicitly how movement flows and the geometry of the layout affect drug dealers spatial decision making. In this chapter, the influence of the configuration of the street network on individual incidents of drug crime placement and the geographical patterning of different types of drug crime were explicitly examined. The general findings are summarised below.

A clear association was found, between street segment length and drug dealing. However, statistically it is also reasonable to expect that the observed number of drug crimes per street segment will increase with the length of the segment, since all things being equal the probability of observing crime per unit length increases with longer streets. In this research, the case study area replicates the geometry of a European type of street network, where long streets represent the core of the network by connecting large-scale movement within the city. It has also been argued (Hillier 2007) that this kind of geometry of the street system facilitates micro-economic activities that take place along the network. Thus, probabilistically it is plausible to assume that more movement and occupation will be generated along the longer lines than the shorter ones per unit length. Considering the proposition (Eck 1995, Rengert et al. 2005) that drug crimes tends to follow some marketing principles similar to retail, where the locations with high volume of potential customers are targeted for the trade, the association of long segments with drug crime sounds plausible.

In line with previous research on drug crime (Eck 1994), it was found that drug dealing locations were associated not only with permeable locations, but also with the locations that are permeable at the regional intra-city scale of movement. Thus, given that a large proportion of the study area is located in a district with active recreational and night-time economy, it is logical to propose that the street network might support opportunities for the regional type of drug market to be established in the area. In Chapter 7, the crime of drug supply is disaggregated according to the drug types and quantities being sold and compared to the level of street permeability. It is assumed that by examining only drug supply locations according to the types of drugs sold per street segments, a spatial retail nature of drug marketplaces can be disclosed. This provides a clarification of the scale and service areas of drug markets being established in the area.

It was found that streets that are one turning away from active retail streets are significantly associated with drug crime. Thus, it appears that the high street might boost the risk of drug crime, but that those streets leading to/from these permeable locations are actually more at risk than the high street itself.

No evidence was found to support the hypothesis that drug production crime could be located on less permeable locations. Conversely, drug production was significantly associated with very permeable streets, such as high streets and also was negatively associated with urban paths and alleys. This might suggest that in the context of the drug production-supply chain, drug production incidents are geographically associated with drug supply locations much more than was initially assumed. Another explanation for this positive result is that the drug production data were still examined at the aggregate level and no distinction was made between different types of drug productions. For instance different patterns may be observed for the production of cannabis, heroin and MDMA.

A significant relationship was found between drug possession locations and local and regional street permeability. Also, local roads were associated with this type of drug crime, implicitly suggesting that residential neighbourhoods account for a large volume of drug possession activity. The connectivity index was negatively associated with drug possession crime suggesting that drug users might avoid big street junctions.

Surprisingly, similar to drug production, drug possession incidents were also negatively associated with urban paths and alleys. It can be suggested that either these types of streets discourage drug possession crime, or that police activity does not target such segments concentrating instead on other roads.
Overall, the results are partially in line with the theory of geographical distribution of crime and rational choice theory.

CHAPTER 6:

The land use mosaic and drug crime: the influence of land uses on drug crime placement

Introduction

The previous chapter looked at ***where*** drug dealing occurs. It was suggested that at the street level of resolution, the spatial configuration of the street network affects the geographical distribution of drug crime. Partial support was provided for the hypothesis that for the study area street network geometry and particularly the level of street permeability would be positively associated with drug crime placement. These findings support crime pattern theory and the proposition (Eck 1994, Rengert et al. 2000) that drug dealers will choose the location where many potential drug buyers can be encountered.

In this chapter, the geographical distribution of drug crime in relation to the urban fabric is further explored. The aim of the chapter is to identify ***why*** some places are attractive for drug crime. It is proposed that in addition to preferring permeable locations, in order to increase drug sales, drug dealers are likely to choose locations that are close to certain facilities or urban activities that attract many more potential customers. For instance, drug dealing locations near transport infrastructure may indirectly increase drug sales, since they facilitate access for a large number of non-residents to the area. Others, such as drinking establishments and recreational clubs generate an atmosphere where illicit drugs are likely to be used. Previous studies, using data mostly for North American cities (Rengert et al. 2000; Eck 1995; Rengert et al. 2005), have found a spatial interaction between criminogenic land uses and drug crime. In these studies, the association was examined by measuring the physical distance between ciminogenic land uses and drug crime locations. The findings of such studies suggest that drug dealing was more clustered near to criminogenic land uses than elsewhere in the city.

However, in this chapter it is suggested that the above-mentioned results may be applicable to the North American style of street network, where movement is generally structured along a uniform grid-like street system. In the current research, this body of knowledge is further extended by examining a similar set of hypotheses for a European style of street network, where movement is structured along a 'deformed grid' street network. The key question is whether similar patterns regarding land use and drug crime interaction hold true for this style of street network. Moreover, in earlier studies, the interaction between land uses and drug crime was measured using Euclidean or 'as the crow flies' distance, in this research an alternative method of measuring criminogenic interaction is presented. Mainly the *street network distance* or walkable distance measure is used, which allows more precise estimation of criminogenic interaction along the street network. Additionally, it is argued that not only does the proximity to specific land uses increase the likelihood of drug crime, but also that the topological positioning of those land uses in relation to permeable streets affects the likelihood of that facility being targeted in comparison to the same type of facility located on less accessible streets. Thus, the research tests whether or not two similar facilities attract equal amounts of drug crime, given that they are located in dissimilar locations of the city. Focusing on the positioning of criminogenic land uses in relation to arterial routes provides additional insight into drug dealer's spatial choices and may allow the development of more effective prevention initiatives.

Chapter 6 is organized: as follows a general background is first presented about drug crime locational preferences in relation to urban activities and land uses (Part 1). The next section presents the main hypothesis and predictions (Part 2). Part 3 describes the geographical distribution of the actual pattern of activities across the Tower Hamlets borough and methodologically shows how these land uses were added to the incident- based street network model. In Part 4, the relationship between different land uses and three types of drug crime is examined using descriptive methods. Next a statistical analysis, which uses event count regression models, is presented (Part 5). Here, for every street segment, the regression models measure cumulative drug dealing opportunity based on the combination of criminogenic land uses present in the area that are within a certain distance of a given street segment. The chapter concludes with a discussion of main findings (Part 6).

6.1 Background

Chapter 6 begins by laying out theoretical dimensions. It discusses criminal decision-making in relation to activity nodes and consequently the influence of routine activity nodes on the clustering of crime in the city. The chapter pursues two aims: first, to determine the extent to which activity nodes in the form of land uses might influence the distribution of drug crime in the city and second, to define the topological extent of this influence, namely whether the specific positioning of these land uses affects the probability of land use being targeted for drug crime.

6.1.1 Routine activity and offender's decision-making

When examining drug crime in the context of Routine Activity Theory, it can be suggested that in order for a drug transaction to occur, a motivated drug dealer should encounter and interact with a potential drug buyer in an urban location that is poorly guarded (Cohen and Felson 1979; Felson 2002). The theory further extends the proposition that the probability of this criminal interaction strongly depends on the drug buyer's and drug dealer's routine activity dynamics in the city, mainly when both routines coincide in time and space, given the absence of capable guardians at the point of convergence. Thus, the encounter and interaction of two individuals in time and space depends on the particular daily routines of those individuals. Hence, changes in their lifestyles will affect the routine activity patterns and consequently the frequency of criminogenic interactions in time and space (Cohen and Felson, 1979).

Many factors affect an individua's routine activity patterns, such as specific goals, mobility constraints, lifestyle, their circle of friends and more. These factors constrain the drug dealer's and drug buyer's spatial-temporal routines to a particular set of *activity spaces*. These activity spaces comprise a geographical area of certain radius, where they go about their daily routines. Scholars have found that offenders and victims tend to share many of the activity spaces that they visit throughout the day in the city (Brantingham and Brantingham, 1993). These are the places where they work, socialize, and go for shopping and recreation purposes. However, an offender's activity spaces may be more diffused than the potential victims are (Brantingham and Brantingham, 1993). For example, while patterns will vary, research suggests that when looking for potential targets, burglars tend to explore adjacent areas up to two blocks away from the main activity spaces where they conduct their daily routines and rarely carry on intended spatial search for targets outside their activity spaces (Rengert and Wasilchick, 1985).

While any activities have the potential to create crime opportunities, places where offenders spend time regularly have more potential to provide opportunities for crime (Felson, 2002). As offenders follow their legitimate daily routine and move along particular routes repeatedly, they develop awareness of these and the criminal opportunities they provide. According to Crime Pattern Theory (Brantingham and Brantingham, 1984), this *'awareness space'* is spatially structured around *activity 'nodes'* that criminals visit throughout the course of the day, *the network of 'paths'* that connect and enable the movement between those nodes, and *the neighborhood 'edges'* - the physical and perceived boundaries that differentiate one area from the other. The offender searches for opportunities and commits crime within this awareness space, close to the principal routes that connect major activity nodes (Brantingham and Brantingham, 1994). Therefore, scholars (*ibid*) have proposed that the juxtaposition of these activity nodes across the street network and the way they are connected creates an '*opportunity network*' for illegal activity. It is assumed that this opportunity network is temporally arranged by routine activity interactions, and spatially constrained by the urban environment. Thus, following routine activity and crime pattern theory, the facilities used in ordinary legitimate activities are predicted to be the most relevant to crime analysis. The following section looks at which facilities are likely to be associated with crime occurrences.

6.1.2 Routine activity nodes and crime concentration

In the city, a considerable part of person's daily routine is centered around certain activity nodes, such as home, work, leisure and others (Clarke and Felson 1979). Commonly these activity nodes are either the exact locations of the facility, such as a school or a shop, or they cover a geographical area with no particular specific destinations, such as visiting recreational or entertainment neighborhoods. Depending on both social and physical context, individual daily routines vary considerably and can cover a geographical area from the local neighborhood to citywide scale. However, at the aggregate level, it is expected that any individual will encounter groups of individuals with similar routines at the same activity nodes in the city. For instance, the likelihood of encountering students and youth near educational land uses is higher than near financial districts. Similarly, office workers can be more commonly seen around business centers than near museum neighborhoods. Thus, land use nodes tend to draw their own group of users either from surrounding neighborhoods, or from the larger spatial scale.

Furthermore, some locations in the city combine several activities; hence many more diverse populations may visit that particular location than other places in the city. For instance, many groups use shopping malls for shopping, entertainment and leisure purposes. Also, a large cluster of different categories of people can be encountered near transit nodes that facilitate the circulation of movement flows throughout the area. Hence, depending on the aggregate routine of urban dwellers, it is expected that certain groups of people will cluster near specific activity nodes. It should be noted that it is difficult to construct the entire routine of an individual or a group of individuals in the city, however the characteristics of the land uses that they are attracted to allow us to make some inferences regarding the aggregate daily routine of those individuals.

Given that different groups of populations will be attracted and spatially concentrated at different street segments, the potential crime profile of those segments will depend on both the type of population visiting and consequently the type of economic and social interactions occurring on those segments (Barntigham and Brantingham, 1993; Eck and Weisburd, 1995). For instance, in the case of drug crime, if the street segments are associated with nighttime entertainment economy, then if it occurs on such a segment, drug crime is more likely to involve the dealing of recreational drugs to groups of people that were attracted to the area for leisure and entertainment purposes.

As discussed, not all places in the city are equally likely to facilitate or be targeted for criminal activity. Scholars suggest (Brantingham and Brantingham, 1995) that the probable crime profile of street segments depends on the type of facilities established on or adjacent to them. They have argued that in the city some urban activities provide conditions that encourage or discourage the concentration of criminal activities. They highlight three land use activity types that determine the likelihood of crime concentration. The first are termed *crime generators* and these describe those urban areas with a mix of activities that attract numerous groups of individuals during their daily routines, including offenders. These locations include shopping streets and centers, entertainment neighborhoods, sport facilities, transport nodes, land uses located on the major movement routes and more. At these locations, the likelihood of a criminal event is the by-product of the large number of people and criminal opportunities generated in the area. Thus, in these places a motivated offender commits opportunistic crime.

The second type of location is termed a *crime attractor* and these represent urban areas or facilities with a reputation that may attract motivated offenders. Offenders are attracted to these places, because of the known opportunities for particular types of crime. These locations can be bars, off-license, car parks; and also can include areas known for non-legal activities, such as red-light districts and drug markets. Offenders come to the area where (for example) alcohol and drugs are being sold or where sex oriented businesses are established with the explicit intent of committing crime.

There is also a third type of location in the city that discourages the occurrence of crime due to enhanced protection or constant surveillance. The courts, police and fire stations are examples of *crime-neutral* places.

Apart from being crime generators or attractors, scholars have suggested (Eck et al. 2007) the concept of *risky facilities*. They argued that facilities of the same type might have very different crime frequencies. This difference may be due to factors such as the social composition of users attracted to the particular facility, the location of the facility in the neighborhood, the place management strategy and so on. Thus, two similar facilities might acquire very different crime risks. They suggested looking at facilities according to their types, i.e. comparing a facility with a high crime rate to another facility of the some type to identify differences in crime risk. In this study, it is proposed that apart from social composition and other factors, differences in crime rates on street segments might be due to the different locational juxtapositions of facilities. This proposition is tested in this chapter.

Together, concepts of crime concentration around facilities discussed suggest that the characteristics of a facility and the way people's routine activities are centered around them can influence whether a given location will become criminogenic, attracting or generating crime.

6.1.3 Drug crime locational choices

For the past 30 years, a consistent relationship has been established between different land uses and drug crime (Roncek and Lobosco, 1983; Roncek and Maier, 1991; Anderson, 1999; Rengert et al. 2000; Groff and McCord 2012). It was found that drug dealing is likely to happen close to facilities, which inherently and routinely generate a large flow of people. These are mainly open public spaces, retail, entertainment facilities and transport interchanges that are associated with low levels of adequate guardianship or place management (Eck and Wartell, 1996). In their analysis, Rengert and colleagues defined two types of built environment facilities that may be associated with the locations of drug markets. First are those that indirectly increase the profits from drug sales, because they facilitate non-residents' access to an area (drug crime generators). An example of this would be transport interchanges, which can provide easy access to drug markets (Brantingham and Brantingham, 1995). Second are those which generate opportunities for drug transactions because they are used routinely by potential drug buyers (drug crime attractors): for example, areas near to homeless shelters or pawn shops where potential buyers can readily convert stolen goods to cash (Anderson, 1999).

Additionally, some scholars have found that drug markets are typically located in close vicinity to certain facilities: shopping centres (Eck, 1995), high schools (Roncek and Lobosco, 1983), bars (Roncek and Lobosco, 1991), cash stores and pawnshops (Anderson, 1999), transport links, train stations and highways (Eck, 1994), and vacant homes (Rengert et al., 2005). Rengert and colleagues (2005) found that some facilities also discourage the establishment of drug markets in an area. These include police and fire stations or courts and federal buildings.

6.1.4 Criminogenic fields and the concept of distance

As discussed, drug-dealing places might be associated with certain types of land uses. It should be noticed that this spatial interaction depends on the proximity and physical accessibility of drug dealing places from the given land uses. In order to study this interaction, theoretical models of criminal spatial behaviour incorporate three key concepts: *proximity to activity space* (Cohen and Felson, 1979), the principle of *least effort* (Zipf 1949; Cornish and Clarke, 1986) and *distance decay* (Journey-to-Crime literature, for the example Rengert, Piquero and Jones, 1999). As discussed, both Routine Activity Theory and Crime Pattern Theory emphasize the role of an offender's routine activity spaces (Cohen and Felson 1979, Brantingham and Brantingham, 1984) in shaping where they commit offences, with locations used routinely being more probable to be targeted for illegal activities. In the context of crime, the least effort concept suggests that there is a trade-off between how far an offender is prepared to travel to commit a crime. According to this proposition, out of several equally attractive available options, an offender will choose the one that involves least effort with maximum outcome. Since more effort, time and money are needed to overcome larger distances, according to the theory, shorter distances will be selected more frequently than longer ones. Thus, the frequency of criminogenic activity will decay with distance from the offender's activity node(s). Consequently, the distance decay concept implies that greater clustering of crime is expected near offender activity nodes than further away. The empirical research consistently has demonstrated this fact (Sherman et al. 1989; Ratcliffe 2006; Johnson et al. 2009; Frank et al. 2011; Birks et al. 2012).

In order to examine the criminogenic effect of legal facilities, earlier studies of drug crime (Rengert et al. 2005, McCord and Ratcliffe, 2007) have used the physical distance from the facility to the nearest crime event as a measure of criminogenic influence. Specifically, the influence of a facility is estimated by examining how much crime occurs around that location, compared to other places. Methodologically, a buffer of a certain radius is drawn near the facility and crime incidents within the buffer calculated. Previous researchers had used the approximate length of a city block to aggregate crime points located near a criminogenic facility into concentric buffers. If there was significantly more clustering of crime near the facility than elsewhere in the neighbourhood, it was assumed that the given facility had a criminogenic effect. Moreover, in this case, it was expected that this criminogenic effect would decrease with distance from the facility. The logic behind the analysis is that the crime incidents that occur near the facility are more likely to be caused by the facility, in comparison to incidents that occur further away. Scholars have found (McCord and Ratcliffe 2007) that drug crime was clustered near the criminogenic facilities considered within two buffers, i.e. up to two blocks. For instance, in Philadelphia being within a street block from a bar or tube station significantly increased the likelihood of drug crime. Thus, scholars concluded that at locations immediate in vicinity of criminogenic facilities there is more crime than of locations that are further away.

As argued above, these studies were conducted using data for regular North American style street networks, where crime is distributed along the grid based street system. Since, pedestrian movement, encounters and consequent transactions are shaped by the arrangement of the street network (Hillier et al. 1993; Hillier 2007), the geographical distribution of drug crime might vary among different street network arrangements. The following sections of this chapter are intended to examine the association between drug crime and urban fabric by examining the specific juxtaposition of land uses that form activity nodes and shape the routines and movement patterns of urban dwellers in a European style of street network. Here the geographical distribution of land uses is used as a filter through which the spatial patterning of drug crime is further explored. In the following section the main hypotheses and research predictions will be presented.

6.2 Current research and predictions

As shown Chapter 5, in the case study area drug crime tended to occur one turning away from permeable streets, such as high streets. It was suggested that drug dealers select the locations in the city where many potential customers can be encountered in less guarded settings. In this chapter, the influence of land uses on crime is examined. In order to further increase the profits from drug trade, it is proposed that drug dealer's spatial choices will be also influenced by specific land uses that attract or generate large numbers of potential customers. Based on previous empirical findings (see below), six land use categories were selected as activity nodes that might have a criminogenic influence. In **Table 1** the land uses are grouped according to the type of routine activity and associated category of users that are attracted to the facility either from surrounding neighborhoods, or from the wider catchment area. The subsequent analysis aims to establish whether or not *proximity - measured in terms of network rather than Euclidean distance - to these activity nodes significantly and positively influences the count of drug crime per street segment.* It examines a set of hypotheses subsequently outlined in **Table 2** by relating the presence of land uses to the locations of drug crime within a certain distance of them (a detailed methodology is presented in Part 3).

The first category of activity nodes shown in Table 1 refers to drinking establishments. Past research (Wadsworth et al. 2004) shows a concurrent addiction of drug users to a frequent use of alcohol. Consequently, several studies (Sherman et al. 1989; Roncek and Maier, 1991) have established a significant increase in the level of crime in neighbourhoods close to locations where alcohol can be purchased, including bars and liquor stores. Therefore, it is expected that drug markets located near to these facilities will profit greatly from potential users visiting drinking establishments. Mainly, it is expected that there will be significant clustering of drug supply and drug possession incidents within the criminogenic field of the facility (in Table 2 hypothesis N1).

Drug markets may also profit from being located near to money lending or other establishments, where potential drug users may convert goods into cash. Researchers (Anderson1999) have found that stolen goods are freely converted to cash in impoverished neighbourhoods of Philadelphia, US. However, this might not be the case in the UK where cash converter establishments closely collaborate with police forces to try to reduce crime (Essex Police[1]). Nevertheless, in this research the distribution of drug supply and possession incidents are examined near money lending shops (hypothesis N2).

Table 1: Activity nodes listed according to the type of routine and potential users

N	Activity node	Type of the routine	Potential users
1	Drinking establishment	Operating mainly after the second half of the day till late night. Serving alcohol accompanied with some sort of entertainment. Usually with weak place management. For this UK study, 'off-license' shops which sell alcohol for home consumption, pubs and bars were counted.	Mostly young population
2	Money lending establishments	Operating during working hours, mostly located on high streets targeting trips that are short in length and are frequently made. Moderate level of anonymity.	People seeking financial micro-lending and cash converting
3	Educational	Operating according to pre-defined term times. Providing compulsory education within a disciplined environment and with constant guardianship.	Youth and students
4	Healthcare	Operating 24 hours. Providing specialised treatment and care. Consisting of a group of buildings freely accessible that attracts patients from the local catchment areas. Low level of adequate guardianship.	Patients, medical staff and visitors
5	Recreational	Mostly used during the daytime. Urban green areas, facilitating both passive and active recreational use. Depending on size, attracting users from local to citywide scale with no particular guardianship.	Any category of people
6	Transportation system	Operating from early morning to late night. Channelling large volumes of people over short and long distances. High level of anonymity.	Any category of people

[1] http://www.essex.police.uk/news_features/features_archive/2013/november/police_join_forces_with_cash_c.aspx [last accessed September 2014]

It is also expected that there will be significant clustering of drug crime near educational activity nodes, such as schools. Although, schools have high levels of surveillance and guardianship, scholars have found that neighbourhoods immediately near to schools suffer from high levels of juvenile crime in comparison to other locations that are further away from schools (Roman 2002; Roncek and Faggiani 1985; Roncek and Lobosco 1983). Here it is hypothesized that drug supply and possession crime may concentrate on the routes leading to and from schools (hypothesis N 3).

University and college establishments are also examined, since it is hypothesized that drug dealers might be attracted to the large number of youth and young adults freely moving across the campus, particularly in urban campus settings, such as in the case study area (hypothesis N 3). Similarly, health establishments, such as large public hospitals are also included as vast numbers of patients and visitors frequent hospitals and there is often low level of adequate guardianship (Fisher 1995; Tomsich et al. 2011) (hypothesis N 4).

Given the high level of anonymity in public parks, it is expected that there will be an association between parks and the possession of drugs (hypothesis N 5) (Knutsson, 1997; Groff and McCord 2012). However, it is not expected that the location of parks and squares will be associated with drug dealing locations, since it has been shown in the Chapter 5 that drug dealers are attracted to more accessible segments where many people pass by, such as high streets.

Drug markets may also benefit from proximity to underground stations, since public transport channels large volumes of people, some of whom are potential drug customers. Environmental criminology research has shown that areas suffering from high levels of crime are often easily accessible to offenders via transportation corridors (Brantingham & Brantingham, 1991). A drug market may therefore prosper from a location near a transportation facility, because of the improved access it provides to its customers. Hence, it is expected that there will be a significant association between drug supply and possession crime incidents and tube stations (hypothesis N6). Drug production cases might also be associated with this facility, since it provides quick access and escape if required.

Apart from examining how proximity to potential crimiogenic land uses influence the count of drug crime per street segment, it is also hypothesized that the close proximity of a facility to the high street will make the latter more prone to drug crime than the same type of facility located further away from the high street. This assumption is based on the finding from Chapter 5, where the presence of the high street significantly increased the count of drug crime on nearby segments. Thus, a comparative analysis of the topological positioning of the same type of facilities in the case study area will be conducted for land uses that are found to have a significant criminogenic effect on drug crime (hypothesis N7).

Table 2: List of hypothesis to be tested in this chapter

N	Hypothesis
1.	Street segments that are located in close proximity to the *drinking establishments* will be associated with drug crime in comparison to segments located elsewhere
2.	Street segments that are located in close proximity to *money lending establishments* will be associated with drug crime in comparison to segments located elsewhere
3.	Street segments that are located in close proximity to *educational land uses* will be associated with drug crime in comparison to segments located elsewhere
4.	Street segments that are located in close proximity to *healthcare land uses* will be associated with drug crime in comparison to segments located elsewhere
5.	Street segments that are located in close proximity to *recreational land uses* will be associated with drug crime in comparison to segments located elsewhere
6.	Street segments leading to/from *transportation facilities* up to a certain walking distance are associated with drug crime
7.	*Criminogenic facilities* that are located closer to the high street will be more associated with drug crime in comparison to those located further away

6.3 The Crime And Urban Mosaic

6.3.1 The Geographical distribution of land uses in Tower Hamlets

Figure 1 shows the distribution of non-residential land uses acquired from the Ordinance Survey AddressBase product in the borough for every administrative ward. It can be seen that the majority of retail land uses (~83%) are located along the high streets. Also, a denser distribution of land uses can be observed in the North-West part of the borough close to London's activity zone. Here, the land uses are distributed mainly across 5 local authority wards - Weavers, Spitalfields and Banglatown, Whitechapel, Bethnal Green North and Bethnal Green South ward.

According to Tower Hamlets council area profiles[2], in the Weavers ward, the Shoreditch quarter has numerous art galleries and a large night-time economy. Also, a flower market is established on Colombia road that attracts many visitors to the ward every Sunday. The Spitalfields and Banglatown wards are famous for their lively and diverse mix of fashion, art, retail and catering uses along Brick Lane and Truman's Brewery. Also, four markets operate in the area during the weekends that draw large number of locals and visitors to the area. At night-time the area becomes a major centre of entertainment with numerous bars and restaurants. The Whitechapel ward with Aldgate area provides a gateway to the City centre with transit movement established in the area. Numerous commercial and office buildings are densely populated in the Aldgate area. One of the central points of the ward is the Royal London Hospital that attracts many patients and medical staff. In comparison to the pedestrian friendly Spitalfields ward, busy vehicular movement passes across the Whitechapel ward facilitating a west-east connection in the borough. The centre of Bethnal Green ward has many diverse shops, catering places and bars. Here, a daily street market operates on Bethnal Green road. Apart from numerous galleries, one of the famous Victoria and Albert museums is located in this ward. Two main traffic connections pass through the area that connects east-

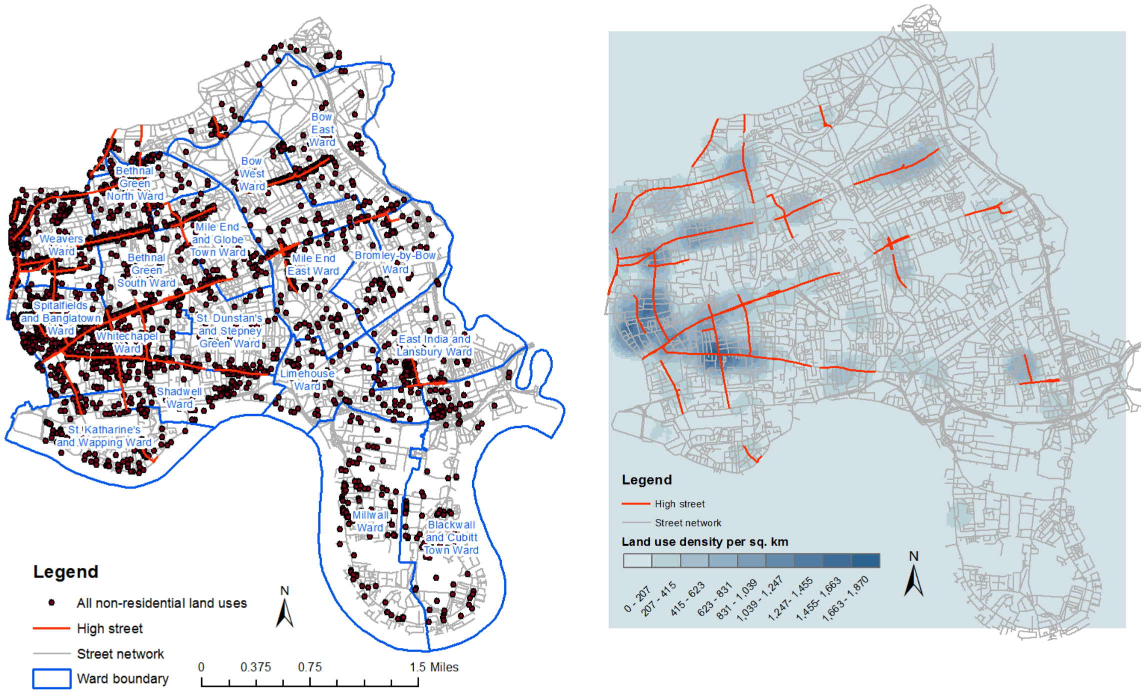
[2] http://www.towerhamlets.gov.uk/lgsl/901-950/916_borough_profile/area_profiles.aspx [last accessed on 7th of September 2013]

west and north-south parts of the borough. In addition to this, two British Rail railway stations and two large parks are located in the area: Weavers Fields and Bethnal Green Gardens.

In the Tower Hamlets borough five wards are bounded by the River Thames – St.Katharine and Wapping, Shadwell, Limehouse, Millwall and Blackwall and Cubitt Town wards. These are mainly residential wards that accommodate a large area of docklands, many of which are redeveloped to residential uses accompanied by bars and restaurants. However, these wards are somewhat isolated from the rest of the borough. For instance, through a single entrance to the Isle of Dogs, the Westferry and Manchester roads are the only highways that pass through the Millwall and Blackwall & Cubitt Town wards. The Canary Wharf business and financial hub is located in the north part of the peninsula, which additionally restricts access to the rest of the island. This is the most commercial area of the borough and is one of the leading financial centres in Europe. It is densely populated with high-rise buildings and has several shopping facilities.

The rest of the wards in the borough are predominantly residential neighbourhoods with small-scale retail centres, such as the area near Mile End Bridge, Roman Road Market in Bow or Chrisp Street market in Poplar. In many cases these neighbourhoods are somewhat isolated by natural or man-made barriers passing through the entire borough. For instance, the east border of the borough is bounded from north to south by the A12 highway leading to Blackwell Tunnel approach. The wards located along this highway are considerably isolated and also have large industrial areas with storage spaces, vacant lands and light-industry. The largest green area of the East End- Victoria Park is located in the north-east corner of the borough. It is actively used throughout the year for different events and festivals. In the middle of the borough, the sequence of Mile End Parks stretches from Victoria Park in the North almost to Limehouse Cut canal in the South. The borough has 46 parks and squares and 2 cemeteries are spread across the wards. Overall, the area of Tower Hamlets has densely populated and overlapping layers of activities, which are non-uniformly distributed across the borough.

Figure 1: Distribution of non-residential land uses (n = 3,756) across the street network per administrative ward



Source: map created based on OS AddressBase® product

6.3.2 Aggregating land uses to street segments

A detailed land use dataset was obtained from the OS AddressBase® product. The data include geocoded point locations of 3,756 land usages for the entire Tower Hamlets area. Table 3 shows the 41 categories of land uses included. It can be seen that more than 80% of the land use in the area is of the retail category, which includes bars and restaurants. Based on the literature review and the list of hypotheses, 6 primary land use categories were selected as independent variables. Hereafter, only these 6 categories will be referred to as land use; the remaining 35 categories are discarded.

These 6 categories of activity nodes were snapped to nearest street segment edges. Any points that were located more than 20m from a street segment were excluded from analysis. Those segments with a particular facility were coded as '1' for having at least one of the given land use type (zero otherwise). Apart from parks and cemeteries, the same procedure was repeated for the rest of the categories. Parks, squares and cemeteries are not directly constituted as part of the streets and physically occupy large geographical areas that often cover considerable proportions of streets and paths. Thus, the park centroids could not be assigned to the closest segments, since nearby segments are also a part of the park. Instead, the physical boundary of the park was identified and all the segments that were within the boundary were coded as '1' under the park category (zero otherwise).

Table 3: All non-residential land use in Tower Hamlets borough (n = 3,756)

Name	Count	%	Name	Count	%
Retail*	3114	82.9	Advice centre	8	0.2
School*	92	2.4	Police station	8	0.2
Religious centre	82	2.1	Educational centre	7	0.1
Park*	46	1.2	Clinic	6	0.1
Community centre	42	1.1	Fire station	6	0.1
Children's playground	31	0.8	Association	5	0.1
Health centre	31	0.8	Charity	5	0.1
College*	28	0.7	Day centre	3	0.07
Tube*	26	0.6	Hostel	3	0.07
Nursery	24	0.6	Museum	3	0.07
Sport	24	0.6	Sail	3	0.07
Administrative	22	0.5	Ambulance station	2	0.05
Children's centre	22	0.5	Cemetery*	2	0.05
Hospital*	21	0.5	Family centre	2	0.05
Recreational	15	0.3	Administrative	1	0.02
Youth centre	15	0.3	Farm	1	0.02
Care home	12	0.3	Health centre	1	0.02
Social club	11	0.2	Recycling centre	1	0.02
University*	11	0.2	Society	1	0.02
Cultural centre	9	0.2	Training centre	1	0.02
Library	9	0.2			

* Land uses used in this study

In order to test the hypotheses listed in the **Table 2**, two different groups of predictor variables are calculated:

1. The potential criminogenic field of each land use within a certain walkable distance
2. The distance from the high street of every street segment that has or is in close proximity to a criminogenic land use.

As discussed, the potential criminogenic effect of a particular legal land use can range up to a certain distance away from the given facility, thus the neighbouring streets might also be affected and have significant clustering of crime. Therefore, the first set of independent variables identifies all neighbouring and physically permeable segments up to a certain metric distance from segments that had at least one of the land uses listed in Table 3.

Since the high street attracts the greatest number of movement flows in comparison to the rest of the streets in the borough, it was assumed that its location would be a good anchoring point to which all other land uses would be linked. Thus, the second set of independent variables reflect the relative positioning of the land uses and nearby segments in relation to the high street: the walkable metric distance was measured from a given land use to the nearest high street intersection.

In order to derive these variables, methodologically, an important distinction was made regarding the concept of distance. The next section details the method of distance calculation.

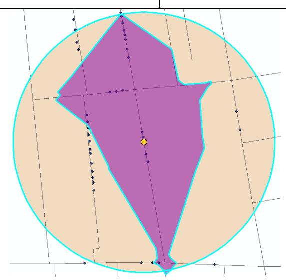
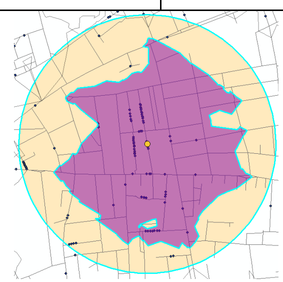
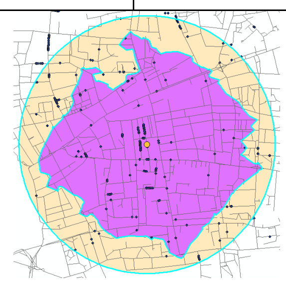
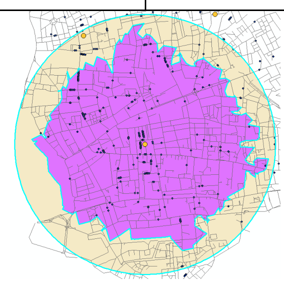
6.3.3 Euclidean vs. network shortest metric distance

In previous studies (Ratcliffe 2007; McCord Ratcliffe 2009; Rengert et.al. 2000) in order to calculate the crime counts near a particular facility or location, the crime counts are aggregated into the buffer and an inverse distance weighting applied to crime incidents, where it is assumed that the strength of the criminogenic influence is proportional to the inverse distance away from the facility. However, this method is not always precise in capturing the potential interaction between a facility and incidents of crime. Since the method uses Euclidean distance to draw buffers around the land use, it assumes that crime incidents are distributed in Euclidean space where all locations within the buffer are equally accessible from a facility. If the researcher is interested in spatial interaction between a facility and crime, this method can be somewhat misleading. To illustrate, consider an area where the street network has a low connectivity index: a potential drug buyer can be very close (physically) to a drug dealing site, but be relatively remote in terms of accessibility along the street network. In the extreme, one could be (say) 20m away from a facility in Euclidean space, but need to travel miles to reach it along the street network. Thus, the probability of a drug dealer encountering a potential drug buyer does not necessarily depend on how far apart they are in Euclidean distance, but on how many connected street segments apart they are along the street network. Thus, the likelihood of the drug transaction depends on any two locations being connected by physically accessible routes. Also, some areas might be separated by natural or infrastructure barriers (river and railway), thus have no influence on each other. This also reduces analytic robustness when Euclidean metric buffer is used. In this research, the measure of distance used is the *network distance* and it measures the *shortest walking distance* from a given facility to the nearest crime incident location.

To illustrate this issue, **Table 4** compares for buffers drawn from one example facility using *Euclidean* and *network distances* for four different metric radii. It can be seen that the former covers much more area than the latter. Using a Euclidean buffer would suggest that there was much more crime within easy reach of a facility, i.e. more points are counted than there actually are within a certain walkable distance of the facility. In contrast, when the crime counts are standardized by street length, the density of crime near the facility is lower than for the Euclidean buffer.

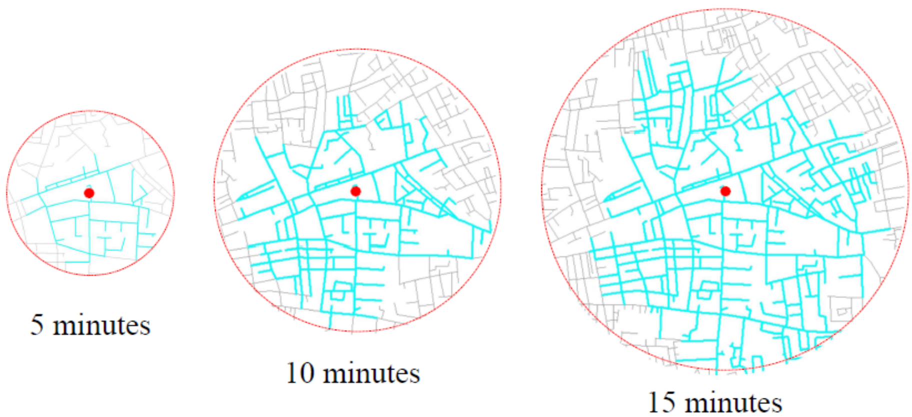
Overall, the Euclidean buffer measures the geographical separation between two locations by constructing abstract straight lines with no reference to the urban features in an area that permit or restrict movement, such as natural or infrastructure barriers. In contrast, network distance is constrained by street network geometry, and thus calculates the distance according to the shortest and physically most permeable travel routes between two points. This is a more realistic quantification of distance, especially for measuring movement or route selection in urban settings.

Table 4: The clustering of drug crime from a facility (marked as yellow dot) calculated using Euclidean buffer (yellow) and network distance buffer (purple) at different metric radii

Buffer radius	**100m**		**400m**		**800m**		**1,200m**	
Distance type	*Eucl.*	*Net.*	*Eucl.*	*Net.*	*Eucl.*	*Net.*	*Eucl.*	*Net.*
Crime count	56.0	53.0	106.0	82.0	210.0	139.0	287.0	252.0
Total length (km)	1.9	0.9	13.6	8.1	51.3	31.4	104.5	68.3
Crime density per km of street	29.4	58.8	7.8	10.1	4.1	4.4	2.7	3.6
Legend Euclidean distance Network distance								

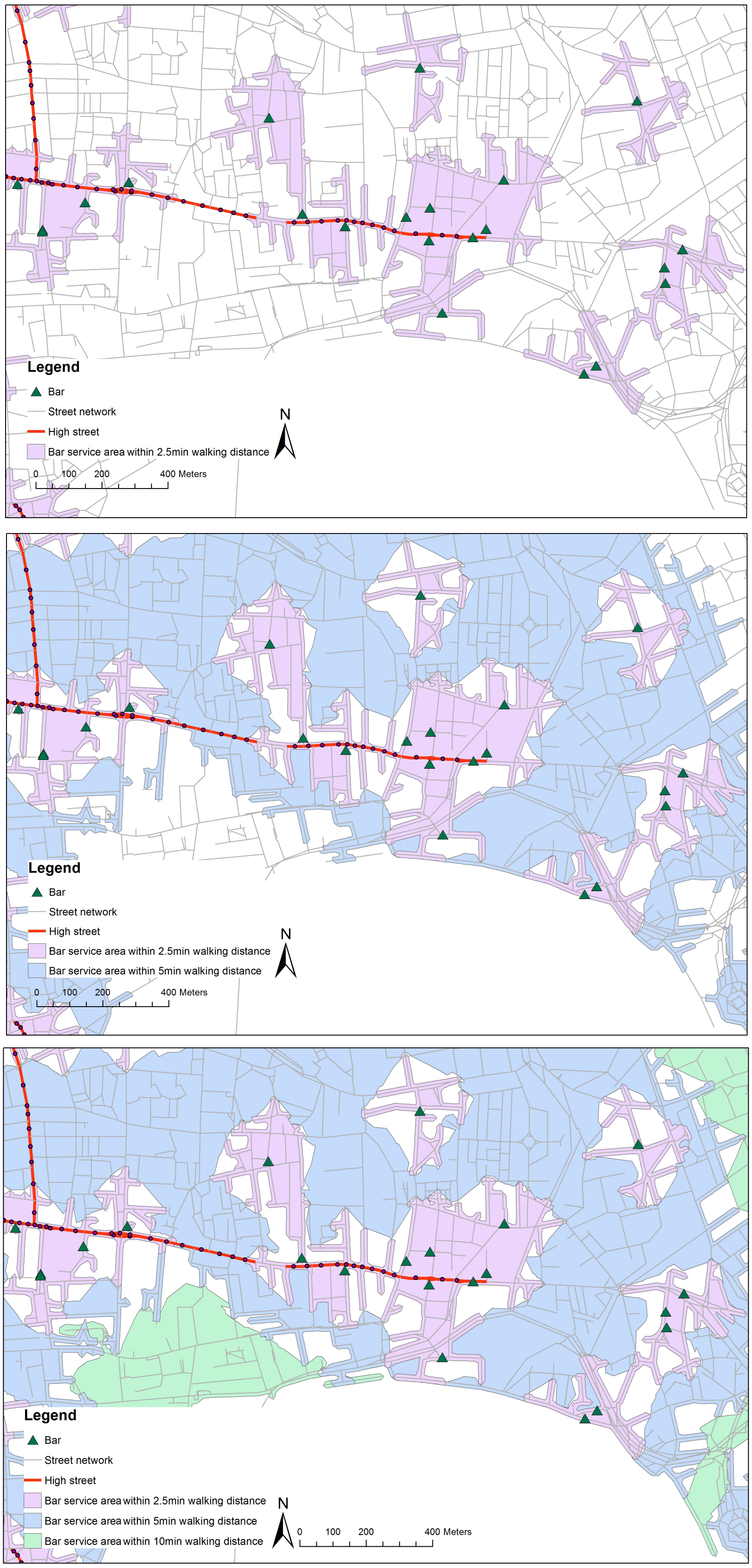
Consequently, in this research the shortest network distance is used as a measure of the criminogenic effect of a facility and it is expected that this effect will decline with distance. Since there are no specific guidelines on how to choose a buffer radius and there is a need to minimise an arbitrary buffer selection, travelling time was used as a proxy measure. Thus, the buffers were chosen according to the time cost spent on traveling between two locations. Expressing the distance covered through a time value, allowed for a more natural conception of distance and perceived adjacency. For this research, the buffer distance selection was informed by average pedestrian movement speed (80 meters per minute) for the London area, where (for instance) 5 minutes of walking approximates to 400 meters distance (Space Syntax Ltd 2009). Three buffer sizes were selected for testing the criminogenic field of a facility: places that could be reached within 2.5, 5 and 10 minutes walk along the street network. These travel times equate to network distances of 200m, 400m and 800m (**Figure 2**) and they were selected to approximate the boundaries of the potential criminogenic affect that a facility might have on the drug crime distribution. It is expected that for drug crime, the criminogenic interaction will be strongest up to 5 minutes walking distance from a facility and will gradually decay after that. Overall, the walkable network distance improves the buffer measure with a more precise proximity component that incorporates both street network space and travel time. Figure 2 provides an example and illustrates dramatically how network and Euclidean buffers differ. For example, for 5 minutes walking distance there is a clear asymmetry in the distance that can be reached from the facility.

Figure 2: Walkable network distance (blue) vs. Euclidean distance (grey) from a facility for different metric distances measured according to *time* cost



Consequently, for the *first set* of predictor variables, three different potential criminogenic fields were calculated using ArcGIS Network Analyst extension (ESRI and Redlands 2006) and binary coded for every corresponding land use. For instance, a segment was coded as '1' if it had at least one bar within 200 meters of a given segment, and '0' otherwise (**Figure 3**). Thus, every street segment in the case study area was coded as '1' or '0' under one of the three categories corresponding to buffers of 0-2.5 minutes, 2.5-5 minutes and 5-10 minutes walking.

Figure 3: Street network buffer distance for up to 2.5 minutes (purple), from 2.5 to 5 minutes (blue) and 5-10 minutes (green) walking from all the bars (marked with green triangle) in the area

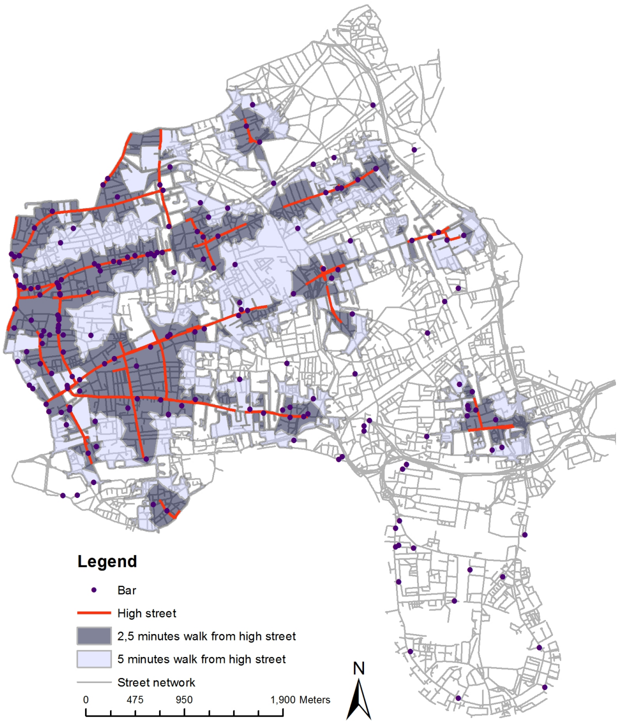


The *second set* of predictor variables measures the juxtaposition of land uses with nearby segments in relation to high streets. Figure 4 shows the shortest network buffer distances from the junctions of the high street[3] and the location of drinking establishments. It can be seen that some bars are located on the high street and others in the adjacent streets, whilst some others are located in the residential hinterland. In order to identify the juxtaposition of segments that have at least one bar facility, a multiple selection method was used in ArcGIS. **Figure 5** illustrates street segments that are simultaneously located within 2 minutes walking distance from the high street and drinking establishments (left figure) and the segments that are located away from the high street, but within 2 minutes walking distance from the bars (right figure). The segments were binary coded. The same procedure was applied to the other categories of land uses.

Overall, the first set of predictor variables show all street segments that are a certain distance away from particular criminogenic land uses, and the second set of variables identify the locations of segments in relation to both high street and particular land uses. In conjunction with the police data this allowed the construction of a database where every given street segment had information on land use type, how far it is located from both the land use(s) and high street and whether or not it has had any drug crime incident(s). The next section examines descriptively the interaction between drug crime, land uses and the high street.

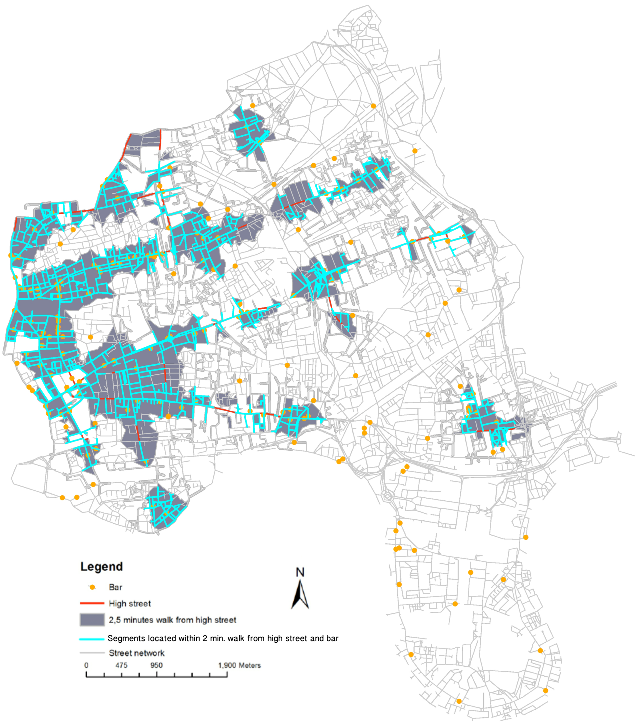
[3] Gort Scott and UCL Bartlett School of Planning 2010

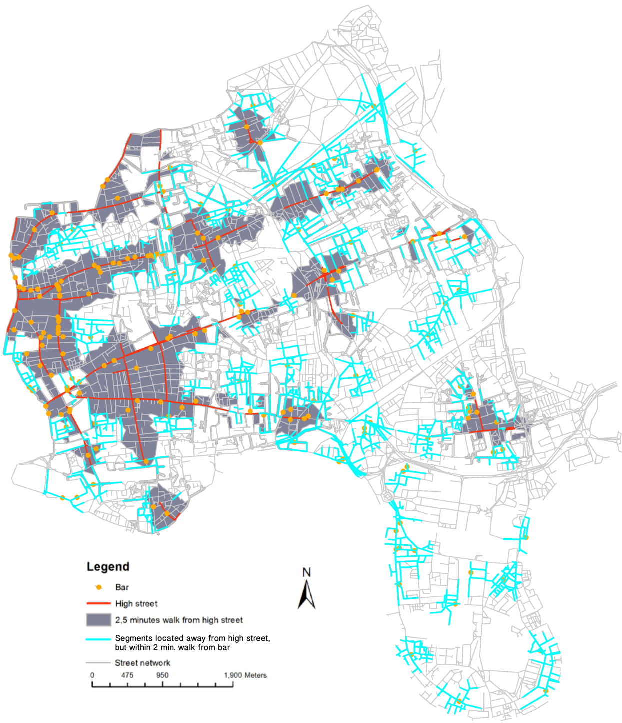
Figure 4: The location of drinking establishments in relation to high streets with 2.5 minutes and 5 minutes walking distance buffers



Source: The location of high streets was identified from the study by Gort Scott and UCL Bartlett School of Planning (2010).

Figure 5: Street segments that are simultaneously located within 2 minutes walking distance of a high street and drinking establishments (*left*) and segments that are located away from a high street, but within 2 minutes walking distance from bars (*right*)





6.4 Descriptive analysis

6.4.1 Juxtaposition of the land uses in the borough

In this section the location and frequency of activity nodes in the case study area in relation to the high street are examined descriptively. **Table 5** and **Figure 6** show the frequency of land uses aggregated to four buffer distances representing the walking distance from the high street. It can be seen that overall most of the facilities can be reached from the high street within 10 minutes walk. Apart from the tube stations, very few facilities are located elsewhere on the network. It can be seen that more than 80% of drinking establishments are located within 2.5 minutes walking distance of the high street. A similar trend is observed for healthcare facilities, universities and money lending establishments, where more than 60% of the respective facilities are located within 2.5 minutes walking from high street. In contrast, schools are almost evenly distributed across the four buffer distances, though more than 90% of them are located in adjacent neighbourhoods within 10 minutes walking distance from high streets. Only tube stations are distributed somewhat equally across the case study area.

Table 5: Land use count within 2.5, 5 and 10 minutes walk from high street and elsewhere

Activity node type (n)	Land use **count** away from high street			
	2.5min	5min	10min	Elsewhere
Drinking establishment (185)	116	30	19	20
Money lending establishment (10)	10	0	0	0
Healthcare use (21)	18	2	1	0
Transportation system (24)	10	2	3	9
Educational use: school (91)	32	28	27	8
Educational use: university/college (39)	30	5	1	3

Figure 6: Cumulative percentage of land use count within 2.5, 5 and 10 minutes walk from high street and elsewhere (the calculation is detailed in **Appendix 4, 5**)

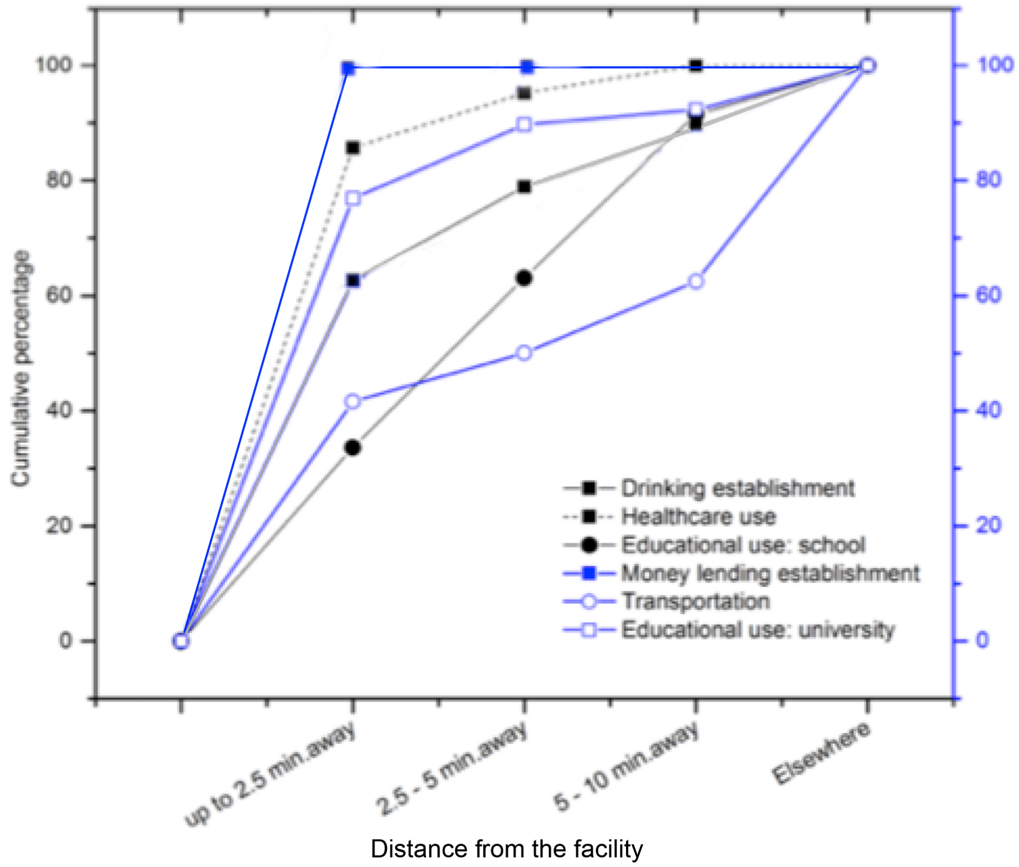
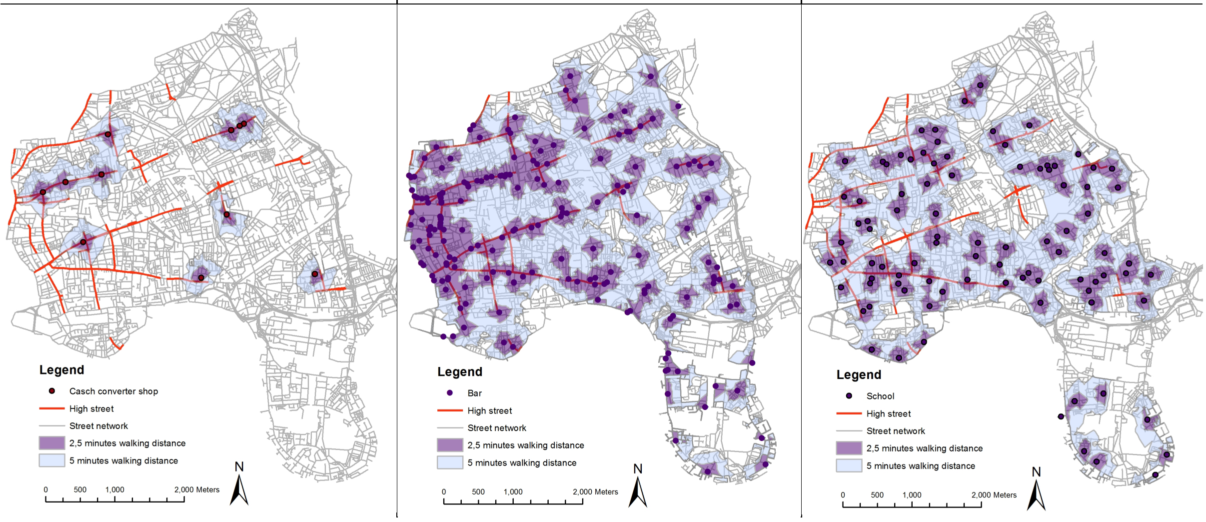


Figure 7 shows the potential criminogenic field of three different facilities. These land uses are similar in their likelihood of having a relatively small catchment area: it is assumed that the population residing in the nearby street segments will use these facilities more than the people visiting the area. From the Figure it can be seen that money-lending facilities are only located along the high streets and their service areas are limited to local street segments, though visitors from other neighbourhoods should not be discounted for this type of facility.

Figure 7: Service area of land uses within 2.5 and 5 minutes walk from 3 different types of land use (2.5 and 5 min. walk covers 200 and 400m distance for London area, correspondingly)

Money lending establishment	Drinking establishment	Educational use: school

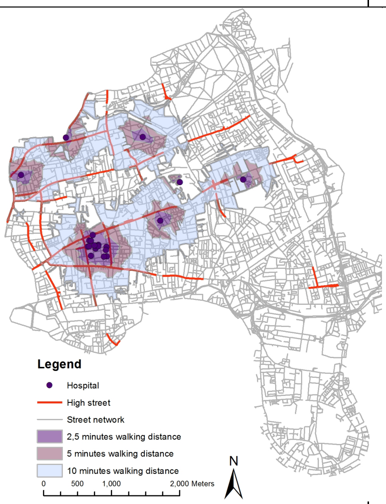


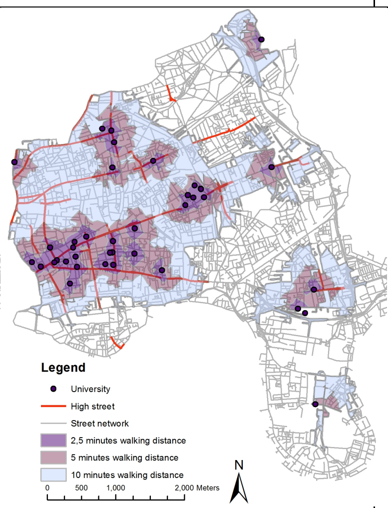
The drinking establishments are densely clustered along the high street, especially on the west side of the borough, where the main entertainment area is concentrated. It can be seen that there is an overlap in many potential criminogenic fields from the drinking establishments, where within 2 minutes walk multiple bars can be encountered. It should be noted that this agglomeration of drinking establishments will most likely attract visitors that make regional scale journeys and the individually located bars will attract a population that makes small-distance journeys. In comparison to drinking establishments, schools are more evenly distributed in the borough, mainly within the residential neighbourhoods adjacent to high streets. Similar to the drinking establishments, some schools may have overlapping criminogenic fields, although this is more likely to be a coincidence and not a feature of agglomeration, as in the case of bars.

Figure 8 shows those land uses that are more likely to have a large catchment area, where both visitors and inhabitants from the adjacent neighbourhoods will visit the facility. It is hypothesised that if there is a criminogenic influence of these types of activity nodes, they will have a larger coverage of street segments, where both locals to the area as well as visitors move to and from the facility. The healthcare facilities are mainly concentrated in the north-west part of the borough near the high street segments. Although hospitals are assumed to provide services across a large area, they are not accessible for the population that resides in the Isle of Dogs part of the borough (south-east peninsula on the map). University and college campuses are also predominantly located along the high streets with large clusters in the west side of the borough. Out of all land uses, only the tube stations are somewhat evenly distributed, facilitating transport access across the borough.

Figure 8: Service area of land uses within 2.5 and 5 minutes walk from 3 different types of land use (2.5, 5 and 10 min. walk covers 200, 400 and 800m distance for London area, correspondingly)

Healthcare use	Educational use: university	Transportation system





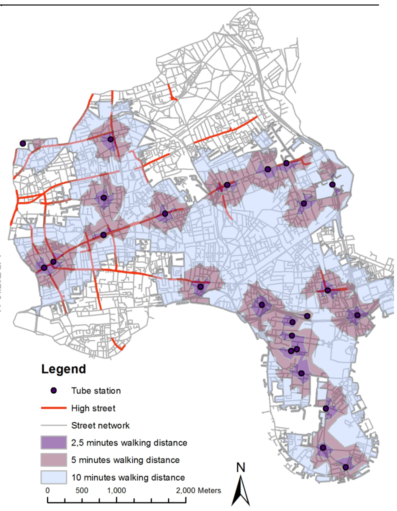
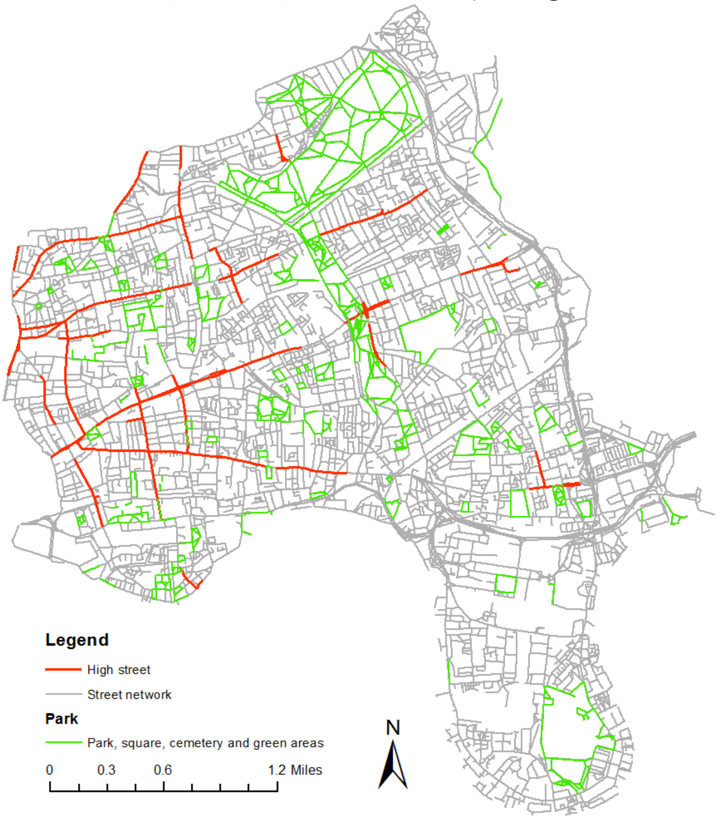


Figure 9 illustrates the location of all recreational areas in the borough including parks, squares and cemeteries. The criminogenic field of this type of land use most probably will be limited to the boundaries of the recreational area itself and depending on the size of the area, its users would be attracted to these activity nodes from anything between a local to a citywide distance.

Figure 9: The distribution of parks, squares, cemetery and green areas in the borough



6.4.2 Land uses and drug crime

This section estimates the frequency of drug crime in relation to the six land use categories. In order to their criminogenic influence, the crime counts on segments that are 2.5, 5 and 10 minutes walk from these land uses were calculated according to formula 1. If T is the total count of crime per distance range k and c_i is the count of crime incidents for drug crime type i, then the total crime count per walking distance range k is calculated as:

$$T_{ck} = \sum_{k=3}^{1} (c_{ik} + c_{i+1k} \dots + c_{nk}) \quad (1)$$

The procedure was repeated for all drug crime types. Next, the density of drug crime count per kilometre of street was calculated for all distance ranges. If L_k is the total length of street network for a given land use category S and C_i is the count of crime for drug crime type i that occurred on the corresponding distance buffer k, then the rate of drug crime per kilometre of network around specific facility is defined as:

$$\mathrm{R}_{Si} = \sum_{k=1}^{6} \left(\frac{C_{ik}}{L_k}\right) \quad (2)$$

That is, total number of crime incidents was divided by the total length of segments located within a certain walking distance from the six different categories of land uses. **Appendix 5** details the exact calculation. Here, the final crime densities from every land use category are plotted according to three distance ranges as shown in **Figures 10, 11** and **12**.

Street segments within 2 minutes walking distance of money lending establishments have high rates of drug crime, although they are only located on the high streets and so the high rates might be attributed to the high street itself. High crime rates are also associated with street segments within 2 minutes walking distance of universities and schools. For these 3 types of facilities, the effect appears to decay with network distance.

This pattern is not repeated for healthcare activity nodes, where similar crime rates are observed up to 10 minutes walking distance, probably indicating either that this type of facility has a large criminogenic field or this is due to the nearby neighbourhoods.

In the case of tube stations, rates of drug supply appear to be supported near to these facilities.

For drug possession crime, for the first buffer, high crime rates can be observed for all categories of land uses apart from hospitals and schools. The rates for the latter category rise after 5 minutes of walking from each land use.

Figure 10: Density of drug *supply* count per street kilometre within 2,5; 5 and 10 minutes walk from six land use types

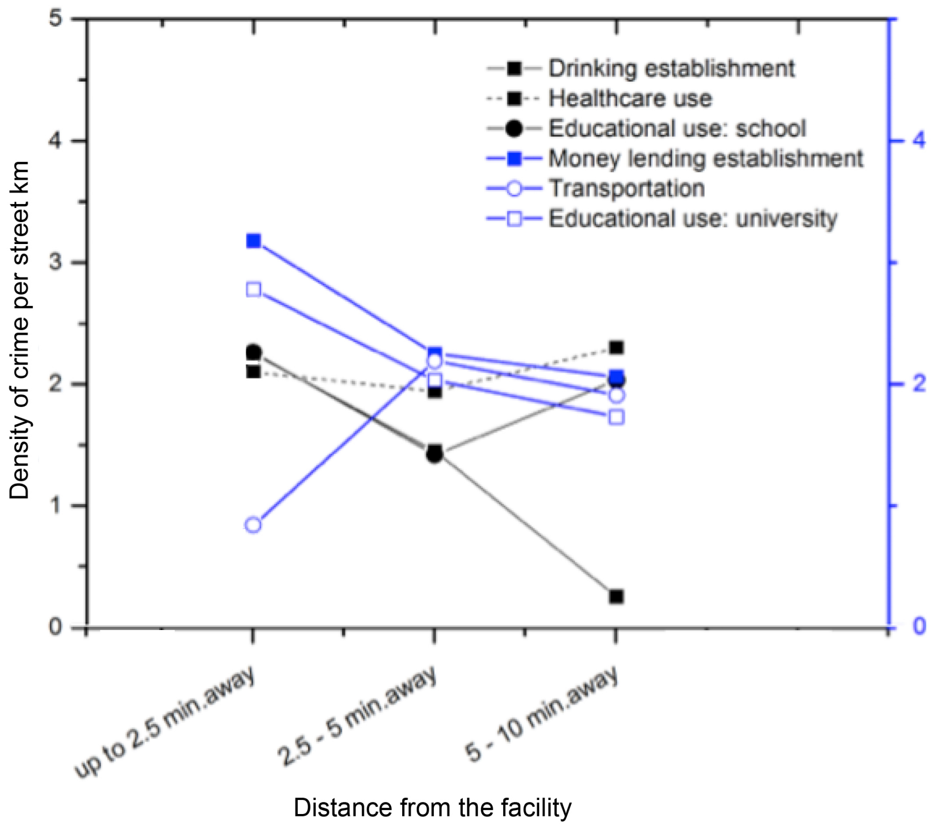


Figure 11: Density of drug *possession* count per street kilometre within 2,5; 5 and 10 minutes walk from six land use types

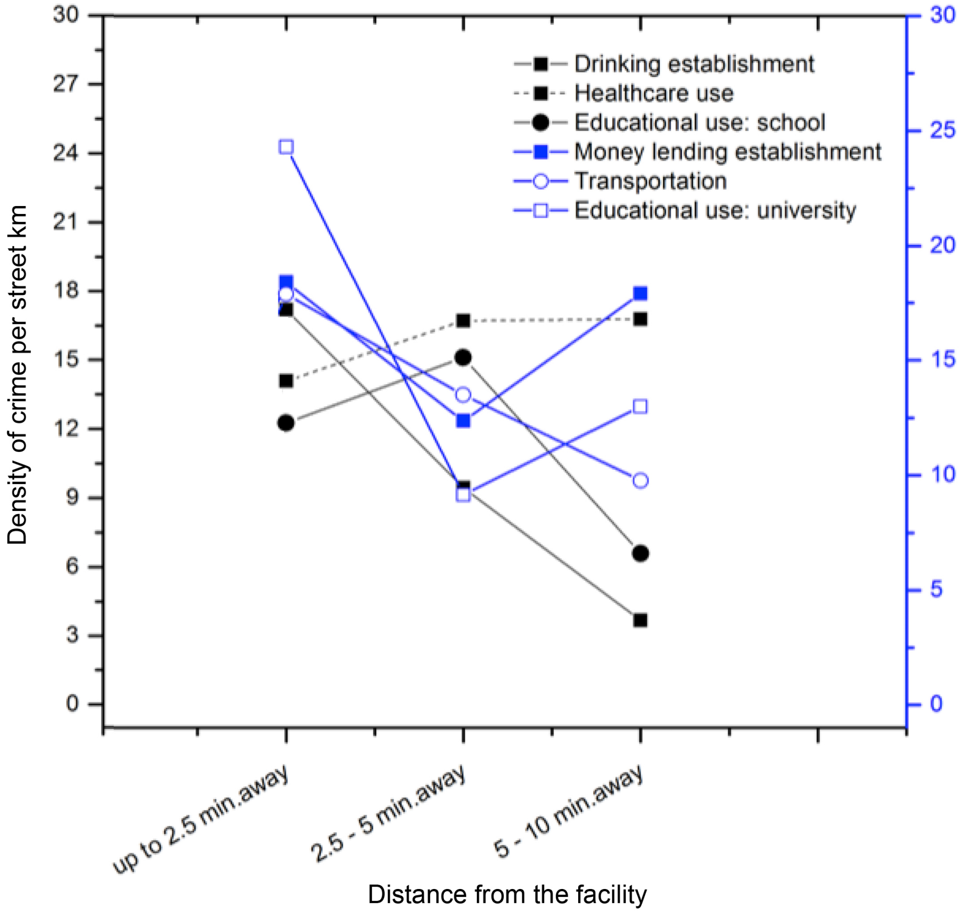
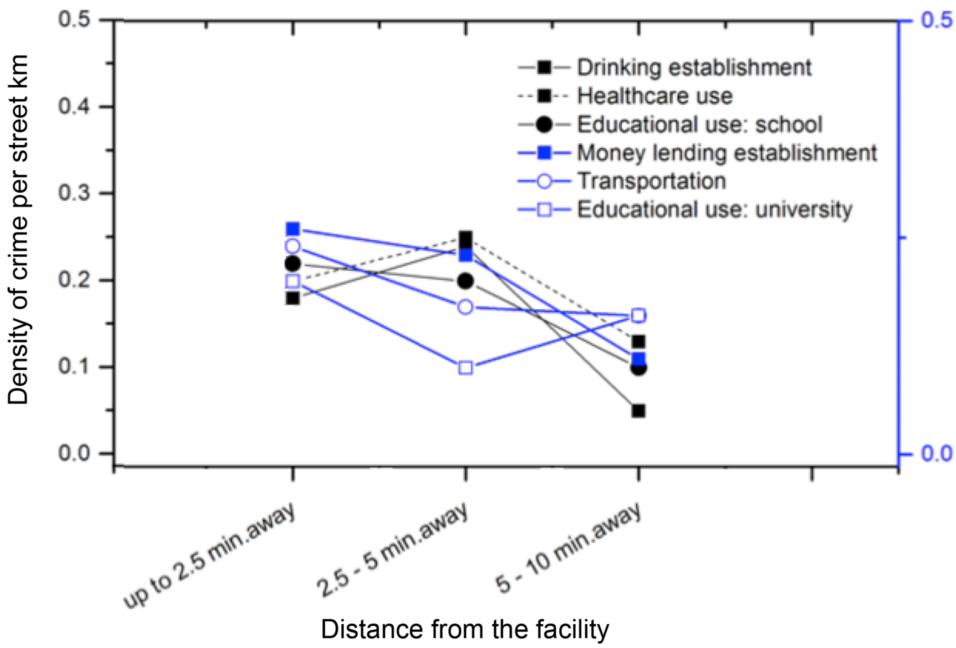


Figure 12: Density of drug *production* count per street kilometre within 2,5; 5 and 10 minutes walk from six land use types



Relatively high drug production crime rates can be observed near transportation and educational land uses, though overall differences are very small. Drug production is less likely to be associated with hospitals and bars.

Table 6 shows the density of drug crime in recreational areas such as parks. Only possession cases appear to be associated with park type of land uses.

This subsection looked at the interaction of activity nodes and drug crime. It identified descriptively the extent of the potential criminogenic fields of different types of land use for every street segment in the case study area. The next part of this section will look at the spatial juxtaposition of these activity nodes in relation to permeable streets, such as high streets, and how this positioning might influence the drug crime profile on nearby street segments.

Table 6: Density of crime per kilometre of segment that is a part of parks, squares and cemeteries grouped according to 3 drug crime categories.

Drug crime	Crime **count**	Segment **length** (km)	**Density** of crime
Supply	66	75.4	0.87
Possession	582	75.4	7.71
Production	12	75.4	0.15

6.4.3 Criminogenic land uses in relation to high street

This part examines descriptively whether the configurational positioning of activity nodes on the street network appears to make both the facility and the nearby street segments more or less risky to crime. It is proposed that the topological extent of the criminogenic influence of a particular activity node is the product of the street network itself. Mainly, it is hypothesized that there will be a positive interaction between the amount of drug crime and facilities located close to permeable streets. Given the findings from Chapter 5, these street segments that are located in close proximity to both high streets and criminogenic land uses are expected to be more prone to crime. For instance, out of the 179 drinking establishments in the case study area, only 20 street segments with bars are prone to drug dealing incidents and from those 20 segments, 16 are located 2 minutes away from high street. That is, they account for 87 % of drug crime that happened on the segments that have drinking establishment and are the riskiest in terms of drug supply crime.

Based on the descriptive analysis (**Figures 10, 11 and Figure 12**) those land uses that had high crime density within 2 minutes walking distance from the facility were selected for analysis. These land uses, with their neighboring street segments, were arranged into two groups: those located within 2 minutes walking distance from the high street or those located somewhere else on the network. Thus, for every drug crime type the land use facility and corresponding street segments were identified. For drug supply crime, drinking establishments and both educational uses were considered. These three land uses had a higher count of crime near the high street than further from it. For drug possession crime, it was drinking establishments, tube stations and universities located close to permeable streets that were examined. For drug production, the potentially criminogenic land uses identified were drinking establishments and tube stations.

Figure 13 compares the ECDF's (described in Chapter 5) for two street segment samples for drug supply and possession crime, in order to test how similar are the two distributions in terms of drug crime count. It was not feasible to calculate the ECDF for drug production cases, due to the small sample size. The first sample is for those segments that are simultaneously located within 2 minutes walking distance from the high street and the specific category of land use. Second are segments that are located away from the high street, but within 2 minutes walking distance from the same type of land use. It can be seen that in all examples, the two distributions differ with more crimes occurring on street segments near the high street. For instance, in the case of drinking establishments 90% of segments that are located away from high street have 2 incident or less of drug dealing, in comparison, 90% streets that are located within two minutes walking distance of the high street have 6 or less crime incidents. Thus, it can be suggested that the street segments located close to both the high street and a particular land use category appear to be targeted more for drug dealing than the ones located further away from high street, but close to the same type of land use.

In the next section, the influence of all land use categories is tested using regression models. **Table 7** summarises the hypothesis to be tested. The initial list of hypotheses is re-examined based on the descriptive statistics obtained so far, mainly **Figures 10,11** and **12** and **Figure 13**. It should be noted that a set of separate hypotheses regarding the proximity to the high street was defined based on the results from the regression analyses. The next chapter examines statistically the interaction between drug crime, activity nodes and high streets at the street segment level.

Figure 13: ECDF of street segments that are simultaneously located within 2 minutes walking distance from the high street and the particular category of land use, or located away from the high street, but within 2 minutes walking distance from the same type of land use.

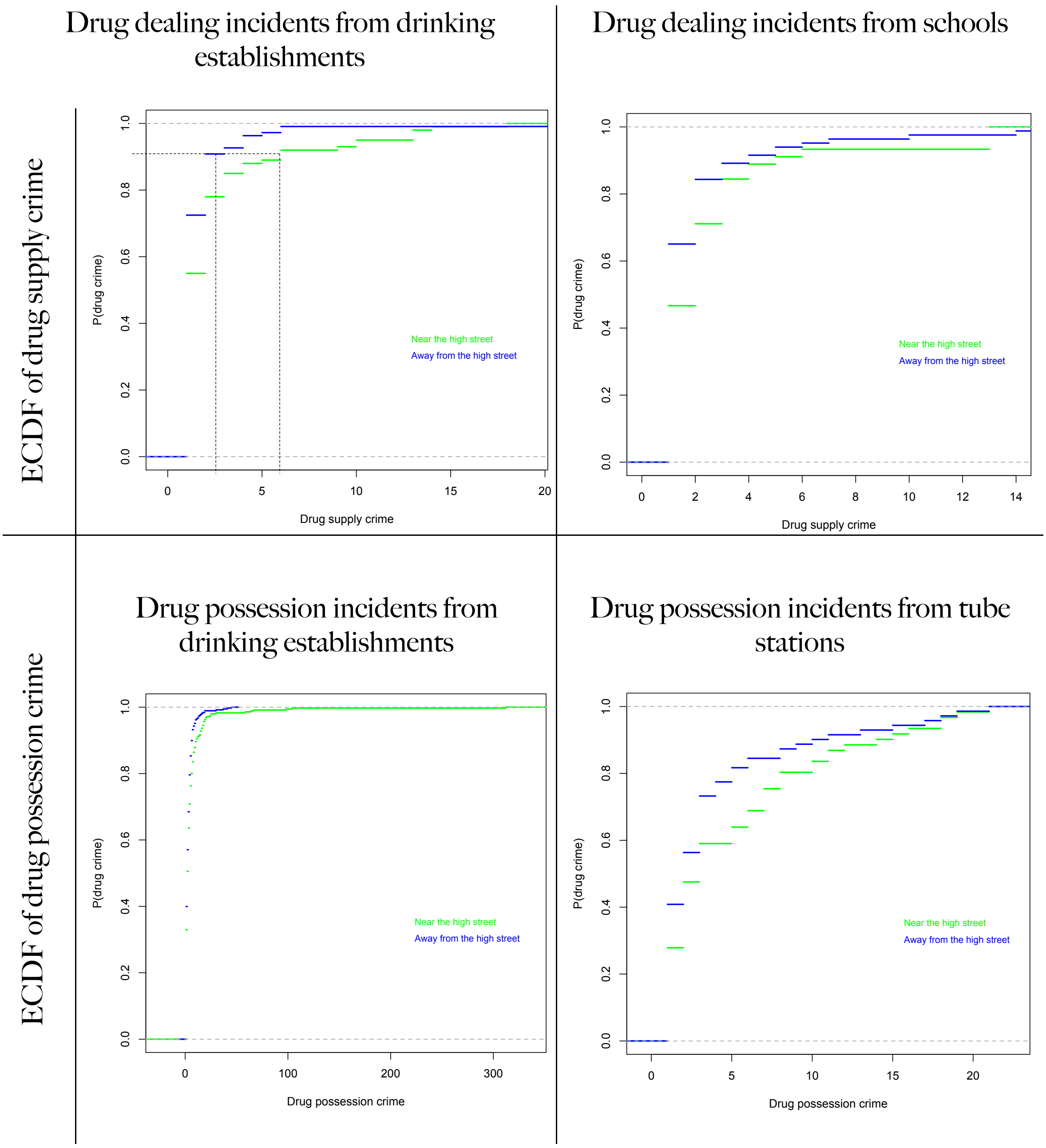


Table 7: Revised list of hypotheses to be tested in this chapter

N	Hypotheses for **drug production** crime
1.	Street segments that are located from 2.5 to 5 minutes walk of ***drinking establishments*** will be more likely to have drug production on them than those that are within 2.5 minutes walk or more than 5 minutes walk from drinking establishments.
2.	Street segments that are located within 2.5 minutes walk of ***schools*** will be more likely to have drug production on them than those that are more than 2.5 minutes walk from schools.
3.	Street segments that are located within 2.5 minutes walk of ***tube stations*** will be more likely to have drug production on them than those that are more than 2.5 minutes walk from tube stations.
N	**Hypotheses for drug supply crime**
1.	Street segments that are located within 2.5 minutes walk of ***drinking establishments*** will be more likely to have drug dealing on them than those that are more than 2.5 minutes walk from drinking establishments.
2.	Street segments that are located within 2.5 minutes walk of ***schools*** will be more likely to have drug dealing on them than those that are more than 2.5 minutes walk from schools.
3.	Street segments that are located from 2.5 to 5 minutes walk of ***hospitals*** will be more likely to have drug dealing on them than those that are within 2.5 minutes walk of hospitals or more than 5 minutes walk from hospitals.
4.	Street segments that are located from 2.5 to 5 minutes walk of ***tube stations*** will be more likely to have drug dealing on them than those that are within 2.5 minutes walk of hospitals or more than 5 minutes walk from tube stations.

5.	Street segments that are located within 2.5 minutes walk of ***money lending shops*** will be more likely to have drug dealing on them than those that are more than 2.5 minutes walk from money lending shops.
6.	Street segments that are located within 2.5 minutes walk of ***universities*** will be more likely to have drug dealing on them than those that are more than 2.5 minutes walk from universities.
N	Hypotheses for **drug possession** crime
1.	Street segments that are located within 2.5 minutes walk of ***drinking establishments*** will be more likely to have drug possession on them than those that are more than 2.5 minutes walk from drinking establishments.
2.	Street segments that are located within 2.5 minutes walk of ***schools*** will be more likely to have drug possession on them than those that are more than 2.5 minutes walk from schools.
3.	Street segments that are located from 5 to 10 minutes walk of ***hospitals*** will be more likely to have drug possession on them than those that are within 5 minutes walk of hospitals or more than 10 minutes walk from hospitals.
4.	Street segments that are located within 2.5 minutes walk of ***tube stations*** will be more likely to have drug possession on them than those that are more than 2.5 minutes walk from tube stations.
5.	Street segments that are located within 2.5 minutes walk of ***money lending shops*** will be more likely to have drug possession on them than those that are more than 2.5 minutes walk from money lending shops.

6. Street segments that are located within 2.5 minutes walk of *universities* will be more likely to have drug possession on them than those that are more than 2.5 minutes walk from universities.

7. Street segments that are located in recreational areas, such as ***parks, squares*** and ***cemeteries*** will be more likely to have drug possession on them.

6.5 Statistical analysis and results

6.5.1 Statistical modelling and diagnostic methods

In order to test the hypotheses set out in **Table 7,** namely to establish a functional relationship between drug crime, activity nodes and high streets, several regression analyses were conducted. Here, the dependent variables were the counts for the three types of drug crime aggregated to street segments, and predictor variables were the presence or absence of specific activity nodes and their topological positioning in relation to high streets. Street segment length was included as a contol variable, since all else equal, there will be more opportunity for crime on longer streets. Prior to regression analysis, several diagnostic tests were performed in order to evaluate both the dependent and independent variables, to see if they violated the assumptions of the regression model, and consequently to decide what regression model(s) to use for hypothesis testing. The following section describes every test separately and presents the corresponding results obtained using CrimeStat III software (Levine, 2010). For a detailed explanation of the diagnostic test and regression model used please refer to Chapter 5 Section 4.

6.5.2 Results from diagnostic tests

Since the dependent variable is the same drug crime dataset that was used in Chapter 5, the diagnostic test results for this variable are the same as described in the Chapter 5, section 4, Table 21 (p.215). Consequently, only the 17 predictor variables are diagnosed as to their suitability for analysis using the pseudo-tolerance test (for the test description refer to the Chapter 5 Section 4). **Table 8** lists all the variables that were used in the regression model, with their corresponding descriptive summaries. Segment length is a continuous variable. The rest of the variables are binary.

Table 8: Descriptive summary of all the variables used in the regression (n = 13,153 street segments)

	Dependent variable	Mean	Standard deviation	Minimum value	Maximum value
1.	Segment production crime count	0.01	0.09	0.00	3.00
2.	Segment supply crime count	0.06	0.57	0.00	32.00
3.	Segment possession crime count	0.44	5.01	0.00	387.00
	Independent variable				
1.	Segment length	39.42	40.67	0.02	400.30
2.	Segments from bar *up to 2.5 minutes walk*	0.37	0.48	0.00	1.00
3.	*from 2.5 to 5 minutes walk*	0.50	0.50	0.00	1.00
4.	*from 5 to10 minutes walk*	0.23	0.42	0.00	1.00
5.	Segments from tube *up to 2.5 minutes walk*	0.09	0.28	0.00	1.00
6.	*from 2.5 to 5 minutes walk*	0.22	0.41	0.00	1.00
7.	*from 5 to10 minutes walk*	0.44	0.49	0.00	1.00
8.	Segments from cash converter *up to 2.5 min. walk*[4]	0.03	0.19	0.00	1.00
9.	Segments from school *up to 2.5 minutes walk*	0.26	0.43	0.00	1.00
10.	*from 2.5 to 5 minutes walk*	0.48	0.49	0.00	1.00
11.	*from 5 to10 minutes walk*	0.35	0.47	0.00	1.00
12.	Segments from university *up to 2.5 minutes walk*	0.15	0.35	0.00	1.00
13.	*from 2.5 to 5 minutes walk*	0.29	0.45	0.00	1.00
14.	*from 5 to10 minutes walk*	0.64	0.47	0.00	1.00
15.	Segments from hospital *up to 2.5 minutes walk*	0.09	0.29	0.00	1.00
16.	*from 2.5 to 5 minutes walk*	0.27	0.44	0.00	1.00
17.	*from 5 to10 minutes walk*	0.72	0.44	0.00	1.00
18.	Segments in parks, squares and cemeteries	0.12	0.33	0.00	1.00

For the predictor variables, a diagnostic test of multicolinearity for the 17 independent variables was performed. **Table 9** shows the pseudo-tolerance tests and the corresponding variable selection procedure used to specify the regression model(s). It can be seen that in total, 5 tests of pseudo-tolerance were performed. The tests are grouped according to three distance ranges. In the first model, all 7 variables representing segments within 2.5 minutes walking distance from facilities were included in a single test. It was assumed that if there is no multicolinearity among these variables, all would be included a single regression model. CrimeStat software automatically outputs the tolerance values for corresponding independent variables and indicates whether or not there is multicolinearity. It can be seen that

[4] there are no cash converter shops beyond high street that is why the variable is omitted for the larger distances

the first model is unreliable, since some variables have low tolerance values, mainly 2.5 minutes walking from bar, from cash converter and from university. The tolerance values indicate that these variables are correlated with each other. A rule was adopted to exclude the highly correlated variables from the model in order to reduce multicolinearity. Following this rule, in the second model, only variables with the highest tolerance value were analysed. With one variable removed, the test showed no apparent correlation between the predictive variables, thus they were assigned to the first model of regression, see **Table 10.** Similar logic was applied to next two groups of variables representing segments that are 5 and 10 minutes walking distance from the land use.

Table 10 lists the final 5 models with corresponding independent variables that will be tested in regression model in the following section.

Table 9: Summary of pseudo-tolerance tests for predictor variables

N	Predictor	Pseudo-tolerance test[1]				
		1	2	3	4	5
1.	Segment length	0.99	0.99	0.98	0.98	0.99
2.	2.5 minutes walking from bar	**0.92**	----	----	----	----
3.	2.5 minutes walking from cash converter	0.95	0.98	----	----	----
4.	2.5 minutes walking from hospital	0.98	0.99	----	----	----
5.	2.5 minutes walking from school	0.98	0.99	----	----	----
6.	2.5 minutes walking from tube	0.98	0.98	----	----	----
7.	2.5 minutes walking from university	0.95	0.97	----	----	----
8.	5 minutes walking from bar	----	----	0.99	----	----
9.	5 minutes walking from hospital	----	----	0.95	----	----
10.	5 minutes walking from school	----	----	0.99	----	----
11.	5 minutes walking from tube	----	----	0.98	----	----
12.	5 minutes walking from university	----	----	0.95	----	----
13.	10 minutes walking from bar	----	----	----	**0.91**	----
14.	10 minutes walking from hospital	----	----	----	0.92	0.96
15.	10 minutes walking from school	----	----	----	0.95	0.97
16.	10 minutes walking from tube	----	----	----	0.96	0.95
17.	10 minutes walking from university	----	----	----	0.95	0.97
	Result of multicolinearity	*Possible*	No apparent	No apparent	*Possible*	No apparent

[1] Predictor with lowest tolerance value in the tested group is highlighted.

Table 10: The predictor variables to be tested per single regression model

Model N	Independent variable(s)
1	Segment length, 2.5 minute walking from cash converter, tube stations, hospitals, schools and universities
2	Segment length, 2.5 minute walking from drinking establishments
3	Segment length, 5 minute walking from drinking establishments, schools, tube stations and universities
4	Segment length, 10 minute walking from drinking establishments, schools, tube stations and universities
5	Segment length, recreational use

6.5.3 Regression modelling of drug production crime

In Chapter 5 it was established that drug production cases appear not to be spatial autocorrelated, thus a Poisson-Gamma regression model was employed. In contrast, both drug supply and possession cases displayed significant autocorrelation, thus the same Poisson-Gamma regression model was selected, but with the spatial autocorrelation component, estimated using the Markov Chain Monte Carlo (MCMC) method. The same procedure of model selection was employed in this chapter as well, given that the same crime data were used. **Table 11** summarises 5 separate models of the Poisson-Gamma regression where the dependent variable was *drug production* incidents and the unit of analysis was the street segment. The first part of the table illustrates five likelihood statistics and two model error estimates that assess the fit of the model. The second part of the table includes estimated coefficients for every predictor variable, plus the intercept.

Initially, the fit of all 5 models were compared. The largest log likelihood value, i.e. closest to zero, was for model N1 followed by N4 model N3. The same models have the lowest information criterion. Although, AIC and BIC penalise when more variables are added to the model, still the performance of models N1 and N4 is equally as good as models that have only one predictor variable, such as models N2 or N5.

The deviance value provides an estimate whether or not the model is over-dispersed. It should be noted that if the model appeared to be over-dispersed then the estimated coefficients might not be reliable, as the standard errors will be underestimated (Levin *et.al.* 2010). Thus, a variable might appear statistically significant when in reality this might not be the case. Overall, the deviance should be smaller than sample size minus the number of independent variables used and plus 1. Among all models, the model N1 has the highest number of independent variables. Given the street segments sample size of 13,153, a value can be computed and compared to the deviance value.

$$13153 - (5 + 1) = 13{,}147$$

None of the deviance values mentioned in the Table 17 is greater than 13,147, therefore there is no over dispersion in the model. The Pearson chi-square also measures the over dispersion in the model. If it is smaller than X^2 value divided by the sample size minus the number of independent variables used and minus 1, then there is no over dispersion detected in the model. The value was calculated for the model N1. It can be seen that the derived value is smaller than 1, thus the model fit is acceptable.

$$\frac{1209}{(13153 - 5 - 1)} = 0.09$$

The model error estimates are quite small for all 5 models.

After accounting for the variation in the segment length, as predicted, street segments that were located within 2.5 minutes walking distance from schools and tube stations were positively and significantly associated with drug crime. No significant association was found between segments that are located from 2.5 to 5 minutes walk away from drinking establishments and drug production locations. However, the results suggest that there may be a potential criminogenic field from other facilities. In the case of schools, it can be seen that there is an association between drug production locations and the presence of a facility on nearby segments up to 5 minutes walking distance away. At locations more than five minutes walk from schools, the reverse appears to be true. In comparison, the criminogenic fields of tube stations appears only to extend up to 2.5 minutes walking distance. The remaining nine predictor variables had no association with drug production crime.

Furthermore, those variables that were significant in Table 17 were further tested in conjunction with the high street variable in order to check whether or not there is a potential joint effect of high street and land use on drug production crime. **Table 12** summarises the list of hypothesis to be tested further.

Table 11: Parameter estimation for 5 separate models of Poisson-Gamma computed using the MLE method, the dependent variable is **drug production** incidents and the unit of analysis is the street segment (sample size n = 13,153 segments)

Summary of goodness of fit statistic	**Model** 1	2	3	4	5
Log likelihood	-496.9	-503.6	-498.7	-496.8	-503.3
AIC	1007.8	1015.2	1011.5	1007.7	1014.7
BIC/SC	1060.2	1045.1	1063.9	1060.0	1044.6
Deviance	481.8***	452.8***	465.8***	454.7***	453.7***
Pearson Chi-Square	1209.0	1043.4	1113.2	1013.9	1062.9
Model error estimates					
Mean absolute deviation	0.01	0.02	0.01	0.03	0.02
Mean squared predicted error	0.11	0.69	0.14	1.61	0.88
Individual predictors	**Coefficients**				
Intercept	-6.30***	-6.01***	-6.53***	-5.66***	-5.96***
Segment length	0.02***	0.02***	0.02***	0.02***	0.02***
2.5 min walk cash converter	0.38 n.s.	----	----	----	----
2.5 min. walk from school	0.67**	----	----	----	----
2.5 min. walk from tube station	0.69**	----	----	----	----
2.5 min. walk from university	0.35 n.s.	----	----	----	----
2.5 min. walk from bar	----	0.07 n.s.	----	----	----
5 min. walk from bar	----	----	0.29 n.s.	----	----
5 min. walk from school	----	----	0.64 **	----	----
5 min. walk from tube station	----	----	0.19 n.s.	----	----
5 min. walk from university	----	----	0.12 n.s.	----	----
10 min. walk from school	----	----	----	-0.58**	----
10 min. walk from tube station	----	----	----	-0.29 n.s.	----
10 min. walk from university	----	----	----	-0.05 n.s.	----
10 min. walk from bar	----	----	----	-0.80 n.s.	----
Park/square/cemetery	----	----	----	----	-0.27 n.s.

*** p <0.001, ** p <0.050

Table 12: List of hypotheses to the potential joint effect of high street and land use on drug crime

N	Hypotheses for **drug production** crime
1.	Street segments that are simultaneously located within 2.5 minutes walk of ***schools*** and within 2.5 minutes walk of ***high street*** will be more likely to have drug production on them than those that are simultaneously located within 2.5 minutes walk of schools, but distant from high street (more than 2.5 minutes walk).
2.	Street segments that are simultaneously located within 2.5 minutes walk of ***tube stations*** and within 2.5 minutes walk of ***high street*** will be more likely to have drug production on them than those that are simultaneously located within 2.5 minutes walk of tube stations, but distant from high street (more than 2.5 minutes walk).

After controlling for the influence of proximity to the high street, when the significant predictor variables from **Table 11** were further modelled with reference to high street locations, a significant result was found for the segments with land uses that were located close to the high street in comparison to those segments with land uses that were further away, see **Table 13**. That is, relative to segments that were not near to tube stations, segments that were simultaneously located in close proximity to tube stations *and* the high street were positively associated with drug production crime.

In the case of the schools, both samples of street segments were positively and significantly associated with drug crime. However, it appears that the effect is larger for street segments that are also near to the high street ($\beta = 0.80$) than those located further away ($\beta = 0.59$).

For both land uses, no significant association was found between segments that were 2.5 minutes away from high streets and drug crime alone, although it should be noted that in **Chapter 5 (Table 20)** a strong effect was found between high street segments and drug production incidents. Given that those segments with tube stations and schools located closer to high street were significant, it can be proposed that there might be an additional effect from high street on the likelihood of drug crime being present on the segments with criminogenic facilities.

Table 13: Parameter estimation for 3 separate models of Poisson-Gamma computed using the MLE method, the dependent variable is **drug production** incidents and the unit of analysis is the street segment (sample size n = 13,153 segments)

Summary of goodness of fit statistic	**Model**	
	1	**2**
Log likelihood	-516.1	-498.2
AIC	1044.2	1008.4
BIC/SC	1089.1	1053.3
Deviance	857.6***	483.8***
Pearson Chi-Square	1216.0	1135.7
Model error estimates		
Mean absolute deviation	0.01	0.01
Mean squared predicted error	0.00	0.00
Individual predictors	**Coefficients**	
Intercept	-5.89***	-6.24***
Segment length	0.02***	0.02***
2.5 min. walk from high street	0.18 n.s.	0.13 n.s
2.5 min. walk from tube station and 2.5 min. walk from high street	1.07**	----
2.5 min. walk from tube station and far away from high street	0.47 n.s.	----
2.5 min. walk from school and 2.5 min. walk from high street	----	0.80**
2.5 min. walk from school and far away from high street	----	0.59**

*** p <0.001, ** p <0.050

6.5.4 Regression modelling of drug supply crime and land uses

Next, analyses were conducted of *drug supply* incidents using a Poisson-Gamma CAR regression model with MCMC estimation that accounts for spatial autocorrelation. Prior to analysis, the model was calibrated in the same way as in Chapter 5. This allowed proper convergence of the model.

The average estimations from all simulation samples drawn are presented in **Table 14**.

Initially, the fit of all 6 models were compared. The largest log likelihood value, i.e. closest to zero, was for model N6 followed by N4 model N1. The same models have the lowest information criterion. Given the sample size of 13,153 and 6 individual predictors, a value can be computed and compared to the deviance value.

$$13153 - (6 + 1) = 13{,}146$$

None of the deviance values mentioned in the **Table 14** is greater than 13,146, therefore there is no over dispersion in the model. The Pearson chi-square also measures the over dispersion in the model. If it is smaller than X^2 value divided by the sample size minus the number of independent variables used and minus 1, then there is no over dispersion detected in the model. The value was calculated for the model N3 that had highest Pearson chi-square value. It can be seen that the derived value is smaller than 1, thus the model fit is acceptable.

$$\frac{6798.5}{(13153 - 6 - 1)} = 0.51$$

The model error estimates are quite small for all 6 models.

Table 14: Parameter estimation for 6 separate models of Poisson-Gamma CAR computed using the MCMC method, which incorporated spatial autocorrelation estimation, the dependent variable is **drug supply** incidents and the unit of analysis is the street segment (sample size n = 13,153 segments)

Summary of goodness of fit statistic	**Model** 1	2	3	4	5	6
Log likelihood	-2031.4	-2051.3	-2066.7	-2017.7	-2050.5	-2002.8
AIC	4080.9	4112.7	4151.4	4051.5	4111.1	4015.6
BIC/SC	4148.2	4150.1	4218.7	4111.4	4148.5	4053.0
Deviance	1683.8***	1781.7***	1741.5	663.1***	1856.5***	1502.9***
Pearson Chi-Square	5344.5	6333.7	6798.5	4662.6	6759.7	3789.6
Model error estimates						
Mean absolute deviation	0.33	0.19	0.35	0.35	0.22	0.61
Mean squared predicted error	77.53	22.15	86.36	18.21	43.94	35.32
Individual predictors	**Coefficients**					
Intercept	-5.58***	-5.55***	-5.94***	-5.69***	-5.02***	-5.01***
Segment length	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***
2.5 min walk from cash converter[1]	1.12***	----	----	----	----	----
2.5 min walk from tube station	-0.97**	----	----	----	----	----
2.5 min walk from hospital	0.29 n.s	----	----	----	----	----
2.5 min walk from school	0.47***	----	----	----	----	----
2.5 min walk from university	0.77**	----	----	----	----	----
2.5 min walk from bar	----	0.88**	----	----	----	----
5 min walk from bar	----	----	0.08 n.s	----	----	----
5 min walk from tube station	----	----	0.57**	----	----	----
5 min walk from hospital	----	----	0.23**	----	----	----
5 min walk from school	----	----	0.50 n.s	----	----	----
5 min walk from university	----	----	0.43**	----	----	----
10 min walk from tube station	----	----	----	0.56 n.s	----	----
10 min walk from hospital	----	----	----	0.76***	----	----
10 min walk from school	----	----	----	-0.29 n.s	----	----
10 min walk from university	----	----	----	0.04 n.s	----	----
10 min walk from bar	----	----	----	----	-1.82**	----
Park/square/cemetery	----	----	----	----	----	-1.07 n.s
Spatial autocorrelation	-0.00 n.s.	-0.00 n.s	-0.00 n.s	-0.00 n.s	-0.00 n.s	-0.00 n.s

*** $p < 0.001$, ** $p < 0.050$

[1] there are no cash converter shops beyond high street that is why the variable is omitted for the larger distances

The regression model shows that, as predicted there is a significant association between the locations of drinking establishments, tube stations, cash converter shops, universities and drug dealing locations. Mainly, those segments that were located within 2.5 minutes from bars, money lending shops and universities and from 2.5 minutes to 5 minutes from tube stations were positively associated with drug supply crime.

The potential criminogenic field from these types of facilities varies depending on the facility type. The criminogenic field of drinking establishments appeared to be limited to the segments located in the immediate vicinity, since the segments located from 5 to 10 minutes away were negatively associated or not significant with drug dealing locations.

In the case of tube stations, the drug dealing was less likely in the immediate vicinity of tube stations, only within 2.5 to 5 minutes walking distance from the stations drug-dealing sites were more likely.

Since, all money-lending shops were located on the high streets, it was assumed that there is no criminogenic field from the facility.

The criminogenic field of the university campus was spread up to 5 minutes walk from the facility. Furthermore, those variables that were significant in **Table 14** were further tested in conjunction with high street variable. The **Table 15** summarises the list of hypothesis to be tested further.

Table 15: List of hypotheses to the potential joint effect of high street and land use on drug crime

N	Hypotheses for **drug supply** crime
7.	Street segments that are simultaneously located within 2.5 minutes walk of ***drinking establishments*** and within 2.5 minutes walk of ***high street*** will be more likely to have drug dealing on them than those that are simultaneously located within 2.5 minutes walk of drinking establishments, but distant from high street (more than 2.5 minutes walk).
8.	Street segments that are simultaneously located within 2.5 minutes walk of ***universities*** and within 2.5 minutes walk of ***high street*** will be more likely to have drug dealing on them than those that are simultaneously located within 2.5 minutes walk of universities, but distant from high street (more than 2 minutes walk).
9.	Street segments that are simultaneously located within 2.5 minutes walk of ***schools*** and within 2.5 minutes walk of ***high street*** will be more likely to have drug dealing on them than those that are simultaneously located within 2.5 minutes walk of schools, but far away from high street (more than 2.5 minutes walk).

When the significant predictor variables from **Table 14** were further analysed in relation to high street segments, similar to drug production cases, a significant result was found for the segments with land uses that were located close to the high street in comparison to those segments with land uses that were further away, see **Table 16.** That is, compared to street segments with a particular facility that are not near to the high street (or those near to the high street without a facility), drug supply offences were more likely to occur on street segments that were located near to both drinking establishments and the high street, or a university and a high street.

In the case of schools, both samples of street segments were positively and significantly associated with drug crime, but those located near to the high street were more likely to have crime on them than those located further away.

Table 16: Parameter estimation for 3 separate models of Poisson-Gamma CAR computed using the MCMC method, which incorporated spatial autocorrelation estimation, the dependent variable is **drug supply** incidents and the unit of analysis is the street segment (sample size n = 13,153 segments)

Summary of goodness of fit statistic	**Model 1**	**Model 2**	**Model 3**
Log likelihood	-1941.9	-1949.8	-1946.4
AIC	3895.9	3911.6	3904.9
BIC/SC	3940.8	3956.5	3949.8
Deviance	1230.6***	1226.3***	1217.7***
Pearson Chi-Square	2046.2	2037.6	1948.4
Model error estimates			
Mean absolute deviation	0.27	0.29	0.37
Mean squared predicted error	23.39	32.62	71.86
Individual predictors	**Coefficients**		
Intercept	-5.00***	-5.05***	-5.05***
Segment length	0.02***	0.02***	0.02***
2.5 min. walk from high street	0.43**	0.70***	0.67***
2.5 min. walk from bar and 2.5 min. walk from high street	0.83***	----	----
2.5 min. walk from bar and far away from high street	- 0.12 n.s.	----	----
2.5 min. walk from school and 2.5 min. walk from high street	----	0.80***	----
2.5 min. walk from school and far away from high street	----	0.34**	----
2.5 min. walk from university and 2.5 min. walk from high street	----	----	1.00***
2.5 min. walk from university and far away from high street	----	----	0.16 n.s.
Spatial autocorrelation	-0.00 n.s.	-0.00 n.s.	-0.00 n.s.

*** p <0.001, ** p <0.050

6.5.5 Regression modelling of drug possession crime and land uses

For incidents of drug possession, the models were examined using a Poisson- Gamma regression model with CAR term that accounts for spatial autocorrelation. Prior to the regression analysis, the model was again calibrated. The number of simulations, the iteration parameters and initial coefficient values were chosen similar to the drug supply model.

The average estimations from all simulation samples drawn are presented in **Table 17**. It can be seen that the largest log likelihood value are for the model N2 followed by N1 and N4. AIC and BIC variable penalising information criterions have the largest values in the models with six variables, such as N1 and N3. Given the sample size of 13,153, the deviance values are smaller than 13,148 indicating that the Poisson model is applicable for the given data structure.

$$13153 - (6 + 1) = 13,146$$

The Pearson chi-square appeared is less than 1 for all six models (for example, model N1 = 0.70 and model N2 = 0.25), thus the model fit is acceptable, no over dispersion is detected. The value was calculated for the model N1.

$$\frac{9311}{(13153 - 6 - 1)} = 0.70$$

The model error estimates are relatively large for all 6 models. The spatial autocorrelation term is not significant showing that the model has successfully accounted for the clustering of the dependent variable.

At the individual variable level, the MCMC model showed that as predicted, those segments that were located within 2.5 minutes walking distance of money lending shops, schools, universities and bars are significantly and positively associated with drug possession crime.

There was a potential criminogenic field from these types of facilities. For drinking establishments, this association appears to be limited to segments located in the immediate vicinity, since segments located 10 minutes away were negatively associated with drug dealing locations. For school facilities, there was a likely criminogenic field for the segments that were located up to 5 minutes walk from the facility.

Also, a significant positive effect was found for segments that were 10 minutes away from hospitals. Parks, squares and cemeteries were negatively associated with drug possession cases.

Additionally, those segments with the facilities that were significant in **Table 17** were further tested in conjunction with high street variable. The **Table 18** summarises the list of hypotheses to be tested further.

Table 17: Parameter estimation for 6 separate models of Poisson-Gamma CAR computed using the MCMC method, which incorporated spatial autocorrelation estimation, the dependent variable is **drug possession** incidents and the unit of analysis is the street segment (sample size n = 13,153 segments)

Summary of goodness of fit statistic	Model 1	2	3	4	5	6
Log likelihood	-7923.8	-7742.9	-8395.2	-7883.7	-7796.0	-7901.0
AIC	15865.6	15495.8	16808.4	15783.4	15602.1	15812.0
BIC/SC	15933.0	15533.2	16875.8	15843.3	15639.5	15849.4
Deviance	7420.8***	6961.0***	8528.7***	7296.2***	7122.5***	7199.1***
Pearson Chi-Square	9311.0	5849.1	1162.5	7268.3	6314.9	8154.1
Model error estimates						
Mean absolute deviation	2.47	3.06	2.77	4.17	3.34	6.48
Mean squared predicted error	453.33	138.00	696.56	374.81	183.17	586.52
Individual predictors	**Coefficients**					
Intercept	-4.04***	-3.96***	-4.45***	-3.89***	-3.46***	-3.64***
Segment length	0.03***	0.03***	0.03***	0.03***	0.03***	0.03***
2.5 min walk from cash converter[1]	1.15**	----	----	----	----	----
2.5 min walk from tube station	$0.03^{n.s.}$	----	----	----	----	----
2.5 min walk from hospital	$0.42^{n.s.}$	----	----	----	----	----
2.5 min walk from school	0.57**	----	----	----	----	----
2.5 min walk from university	1.08**	----	----	----	----	----
2.5 min walk from bar	----	0.82***	----	----	----	----
5 min walk from bar	----	----	$0.07^{n.s.}$	----	----	----
5 min walk from tube station	----	----	$0.26^{n.s.}$	----	----	----
5 min walk from hospital	----	----	$0.56^{n.s.}$	----	----	----
5 min walk from school	----	----	0.66**	----	----	----
5 min walk from university	----	----	$0.39^{n.s.}$	----	----	----
10 min walk from tube station	----	----	----	$0.12^{n.s.}$	----	----
10 min walk from hospital	----	----	----	0.71**	----	----
10 min walk from school	----	----	----	$-0.43^{n.s.}$	----	----
10 min walk from university	----	----	----	$0.14^{n.s.}$	----	----
10 min walk from bar	----	----	----	----	-1.29***	----
Park/square/cemetery	----	----	----	----	----	-1.21***
Spatial autocorrelation	$-0.01^{n.s.}$	$-0.01^{n.s}$	$-0.01^{n.s}$	$-0.01^{n.s}$	$-0.01^{n.s}$	$-0.01^{n.s}$

*** p <0.001, ** p <0.050

[1] there are no cash converter shops beyond high street that is why the variable is omitted for the larger distances

Table 18: List of hypotheses to the potential joint effect of high street and land use on drug crime

N	Hypotheses for **drug possession** crime
1.	Street segments that are simultaneously located within 2.5 minutes walk of ***drinking establishments*** and within 2.5 minutes walk of ***high street*** will be more likely to have drug possession on them than those that are simultaneously located within 2.5 minutes walk of drinking establishments, but far away from high street (more than 2.5 minutes walk).
2.	Street segments that are simultaneously located within 2.5 minutes walk of ***schools*** and within 2.5 minutes walk of ***high street*** will be more likely to have drug possession on them than those that are simultaneously located within 2.5 minutes walk of schools, but far away from high street (more than 2.5 minutes walk).
3.	Street segments that are simultaneously located within 2.5 minutes walk of ***universities*** and within 2.5 minutes walk of ***high street*** will be more likely to have drug possession on them than those that are simultaneously located within 2.5 minutes walk of universities, but far away from high street (more than 2.5 minutes walk).

When the significant predictor variables from **Table 17** were further analysed in relation to high street segments, after accounting for the influence of the high street per se, similar to drug production and supply cases, a significant result was found for segments with land uses that were located close to the high street, see **Table 19.** That is, drug supply offences were more likely on street segments that were located near to both a drinking establishment and a high street, or a university and a high street, than those with the presence of those facilities that are not near to the high street.

In the case of schools, both samples of street segments were positively and significantly associated with drug crime. However, crime was more likely on those located near to the high street influence than those located further away.

Table 25: Parameter estimation for 3 separate models of Poisson-Gamma CAR computed using the MCMC method, which incorporated spatial autocorrelation estimation, the dependent variable is **drug possession** incidents and the unit of analysis is the street segment (sample size n = 13,153 segments)

Summary of goodness of fit statistic	**Model**		
	1	**2**	**3**
Log likelihood	-6833.9	-6847.8	-6873.9
AIC	13679.8	13707.6	13759.9
BIC/SC	13724.7	13752.5	13804.8
Deviance	3636.6***	3595.2***	3600.2***
Pearson Chi-Square	7186.5	8123.5	6967.7
Model error estimates			
Mean absolute deviation	3.04	7.88	5.43
Mean squared predicted error	5097.57	7116.01	2663.77
Individual predictors	**Coefficients**		
Intercept	-3.03***	-3.12***	-3.06***
Segment length	0.02***	0.02***	0.02***
2.5 min. walk from high street	0.36***	0.69***	0.72***
2.5 min.walk from bar and 2.5 min.walk from high street	0.97***	----	----
2.5 min.walk from bar and far away from high street	0.10 n.s.	----	----
2.5 min.walk from university, 2.5min.walk from high street	----	1.16***	----
2.5 min.walk from university and far away from high street	----	-0.09 n.s.	----
2.5 min.walk from school and 2.5min.walk from high street	----	----	0.73***
2.5 min.walk from school and far away from high street	----	----	0.21**
Spatial autocorrelation	-0.01 n.s.	-0.01 n.s.	-0.01 n.s.

*** p <0.001, ** p <0.050

6.6 Discussion

The aim of this chapter was to establish whether or not the criminogenic interaction between urban land uses and drug crime is similar for different types of street segments. It presents an alternative estimation of proximity at the street segment level of resolution and it examines the spatial interaction between land uses, street permeability and drug crime. Previous studies of drug crime have suggested a criminogenic influence of certain types of legal land uses on drug crime. However, they do not examine explicitly the criminogenic field of this influence in relation to the street network, particularly how far from a facility illegal activity is distributed along the street network. Moreover, earlier studies did not analyze the configurational positioning of criminogenic activity nodes in relation to permeable streets and how it might affect drug dealer's spatial target choices. In this research, the extent to which activity nodes influence the distribution of drug crime across the street network is explicitly examined. The general findings are summarized below.

Drug production locations are typically indoor places, thus they should be less associated with the travel patterns of potential buyers. However, their positioning might be more related to permeable locations, such as highways that facilitate ease of access and escape from an area (Eck 1995). In this study, a significant relationship was found between drug production locations and street segments that are located very close (2.5 minutes walking distance) to tube stations. Moreover, only those segments that were located within 2.5 minutes walking distance from both high streets and tube stations were positively associated with drug production locations.

A clear distance decay of criminogenic field from schools was also identified. Drug production was more likely to be established on street segments that are within 5 minutes walking distance from schools, than on segments that were more than 10 minutes walking distance away. Moreover, those segments near schools that were located closer to the high street were more associated with the drug crime than those located near the schools, but further away the high street.

In line with previous research, a significant positive relationship was found between drinking establishments and drug crime on the European style of street network. That is, street segments that were 2 minutes walking distance away from these type of facilities were more likely to have drug-dealing incidents than segments that were further away. However, not all drinking establishments are prone to drug dealing. It was established that only segments near bars that are also located 2 minutes away from permeable streets, such as high streets are significantly associated with drug supply crime.

Those segments that were located within 2.5 minutes walking distance from schools were significantly associated with drug supply. Similar to drug production crime, segments that were located near to schools *and* high streets were more associated with drug crime than those with the presence of the school that are not near to a high street (or those that were near to the high street but not a school).

Similar to drug supply crime, drug possession was more likely on street segments leading to drinking establishments which are located near the high streets.

In line with previous research, money-lending establishments were also associated with drug possession crime. However, it should be noted that the significant effect most probably is due to the fact that all facilities of this type are located on high streets, which have already been established to be associated with drug crime (see, Chapter 5).

In the case of educational land uses, only university campuses located within 2 minutes walk from the high street appeared to affect the location of drug possession crime. No criminogenic association was found for universities located further away from high streets.

Segments located near to schools were positively associated with crime and there was a clear distance decay of the criminogenic field from schools up to 10 minutes walking distance away. Similar to drug supply crime, the segments near schools that were located near the high street were more associated with drug crime than those located further from high street.

With health care facilities, only segments that are within 5 to 10 minutes walk from hospitals were significantly associated with drug possession. No significant crime clustering was found in the immediate vicinity of the hospitals.

To conclude, theories of environmental criminology state that specific types of land uses and facilities generate crime due to the daily activities associated with them and the number and type of people they attract. The above findings suggest that not only the facility itself attracts crime, but the specific configurational positioning of that facility on the street network also influences the likelihood of crime. Specifically, the high street - whether its inherent high permeability or its permeability coupled with its function as an attractor of pedestrian traffic, were not only associated with drug crime, but the activity nodes that were located near this type of street where also more prone to drug crime than those located further away from the high street.

CHAPTER 7

Towards the rationale of drug crime clustering

Introduction

The previous two chapters examined where drug dealing occurs and why these places are attractive for illegal drug crime. It was illustrated that both the layout of the street network and proximity to specific criminogenic land uses appear to have a significant effect on the locations of illegal trading. Hence, the results supported propositions of Crime Pattern Theory and Routine Activity Theory. Moreover, it was suggested that the layout of the street network has more effect on the distribution of drug crime in the city than originally was assumed (Rengert et al. 2005; Eck 1995). It was demonstrated that depending on the position of criminogenic land uses in the street network, the risk of drug crime occurring on them or on nearby segments varies considerably. Specifically, segments with the land uses that were located closer to very permeable streets, such as high streets, were targeted more for drug crime than those segments that were further away.

So far, all incidents of drug crime have been treated as individual occurrences of crime and the relationship between multiple incidents of crime and between different drug types has not been examined. This chapter focuses on the question of ***why*** drug-dealing incidents are arranged as they are and how different types of drug markets might be identified from these arrangements. The chapter examines the reciprocal positioning of drug dealing locations in relation to each other and in relation to the drug types being sold per street segment. For instance, it is proposed that a consideration of street permeability and the types of drugs traded on a street segment might provide a good indicator of what type of market is established in the neighbourhood, i.e. local or regional drug marketplace.

Scholars (Weisburd and Green 1994) have already pointed out that drug markets can vary in their clientele, size and drug types being sold. They propose that dealers will try to establish markets at locations that reduce the total distance that customers will have to travel to reach them. In order to determine the demand for drug markets, US researchers (Rengert et al. 2005) have used methods of socio-demographic profiling to identify those types of neighborhoods with the characteristics that are associated with increased risk of drug use. They propose that if a drug dealer wants to sell drugs to a local community, he must first identify possible users. If the local demand is not enough to sustain a drug market, the dealer must consider factors that would attract potential customers into the neighborhood. For example, the market should be situated in close proximity to transport facilities, which are used routinely by many potential drug addicts, or it should be accessible to modes of private transport.

Despite an extensive research into drug crime, there is a lack of evidence regarding how different types of drugs are being sold on the streets and whether or not there is a geographical relationship between where drugs are being produced and supplied across the street network. This part of the research examines these questions and also looks at how patterns relate to the level of permeability and whether or not local or regional drug markets can be identified.

Chapter 7 is organised as follows: the drug marketplace is presented (Part 1), followed by the discussion of several concepts from urban theories about how legal goods are distributed geographically in the city (Part 2). In Part 3, parallels are drawn with concepts from economic geography, with illegal drug dealing considered a form of a good that is supplied to customers and the main hypothesis are presented. Empirical analyses follow to test hypotheses, and the chapter is concluded with a discussion of the findings (Part 4).

7.1 Drug marketplace

A drug marketplace is where a dealer and buyer meet to exchange drugs for money. Similar to legal markets, drug markets follow basic laws of supply and demand (Rengert et al. 2005). Drugs are sold in a similar manner to other legal commodities. However, unlike legal commodities, illegal drugs are associated with a high risk of legal prosecution, violence from competitors and poor product quality (Eck 1995). As discussed, the drug markets are categorised as closed socially bounded network and open markets that are accessed during peoples' daily routine activities (Eck 1995). There are no barriers to enter open street drug markets, given that the potential customer talks and looks like a drug user. Closed markets are only accessible to recommended drug buyers and are hard to access for new buyers (Eck 1994). Both types of drug market could attract customers from local neighbourhoods, or regional populations residing outside the local area. For example, Eck (1994) found that in San Diego, outdoor drug markets formed at locations about two blocks away from major transportation arteries, suggesting that they were regionally permeable markets. Importantly, this suggests that although offenders aim to sell drugs from permeable locations, they do not tend to do so on major roads (presumably as a way of reducing risk). That is, for regionally permeable markets, operating in close proximity to major roads may offer an acceptable balance of custom and safety (Eck 1994). In comparison, in Philadelphia, Rengert and Ratcliffe (2005) found a high concentration of drug markets located in the suburbs, located away from major roads, suggesting that these marketplaces are oriented to local rather than regional demand.

Street drug dealing will also differ by the type of drugs being sold (Eck 1994, Weisburd and Green, Bean 2014). Research (McSweeney et al. 2008) suggests that there are more drug dealers who specialise in dealing in a single drug commodity than multiple drugs, although there are 'poly dealers' who sell any kind of drug (Bramley-Harker 2001). Such illegal drugs are crack, heroin, cannabis, powder cocaine, methamphetamine, and ecstasy.

Scholars (Eck 1994, Bean 2014) suggest that depending on a drug type, the illegal drug will be sold in variety of locations in the city. For instance, cannabis dealers target a wide variety of population and sell the drug in various locations, from local neighbourhoods to a citywide scale. On the contrary, ecstasy is sold to clubbers near or in the dancing venues. Further, cocaine users are commonly from middle and high class, and the drug is sold in variety of places. It should be noted that all these drugs could be sold both in open and closed marketplaces. Moreover, the way the illicit transaction is organised for the given drug illustrates the solution of the "between access and security" (Eck 1994) dilemma. For instance, scholars (Eck 1994) found that methamphetamine is sold through social bounds, i.e. drug dealers used their network of friends in San Diego. However, cocaine is more likely to be sold to strangers through routine activities (Eck 1994). Or others (Curtis and Wendel 2000) found that across three blocks of New York, crack marketplaces were established by the means of 'freelance' and 'socially bonded' dealing.

Since drug markets may share features with legal markets (Eck 1995), in the next part of the chapter some parallels are drawn with urban theories about the way legal goods are distributed in the city. In the subsequent section it is then proposed that illegal drugs might have similar geographical form of supply as the distribution of legal goods in the city.

According to the retail geography perspective, the distribution of goods and corresponding consumer behavior can be grouped into three main observations (Dawson 2012): the influence of geographical location (Berry and Garrison 1958; Davis 1972b; Davis 1976), the nature of the goods or services provided (Christaller 1933; Rogers 1969) and the shopping travel routine (Golledge and Brown 1967).

At the city level, the geographical patterning of shops is neither random, nor uniform (Lösch 1940; Getis 1967). Most of the shops tend to exhibit spatial regularities in respect to geographical characteristics of the area. Mainly, since the retailer pursues the goal of maximising sales, he would select the most profitable location for the shop that is accessible to many potential customers (Scott 1970). The location of the shop not only requires a permeable location that attracts sufficient number of customers, but also depends on the type of goods that the retailer is intending to sell (Berry and Garrison 1958) and the spatial organisation of the market including the behaviour of competitors (Scott 1970). Additionally, the shop location might be chosen in proximity to complementary facilities, such as the sources of supply or commodity production (Turvey 1957; Lean and Goodall 1966).

At least two kinds of spatial regularities can be observed in the locational preferences of shops in the city (Christaller 1933; Berry 1959). The shops that sell everyday essentials and convenience goods are commonly situated in local neighbourhoods and usually target customer trips that are routinely made from local areas, are short in length and require minimum of effort. These are the shops that sell low rank goods (Berry and Garrison 1958). They tend to have a high degree of spatial dispersion from each other. In contrary, those shops that sell valuable goods or goods that are specialised or bought infrequently will tend to attract purposeful trips that can be made from anywhere in the city. These shops sell high rank goods and tend to cluster together at very permeable locations in the city. For instance, furniture shops will be agglomerated together, where customers can compare between the available options in more than one shop, before purchasing the product.

Scholars (Golledge and Brown 1967) also note that shopping behaviour is constrained by shopper's incomplete knowledge of all the shopping opportunities available in the area. Thus, the consumer will be satisfied making routine trips to known shopping areas that might not necessarily be the most economically beneficial ones.

According to the "nearest centre proposition" (Christaller 1933), during the daily routine, the consumer will most probably visit the closest retail shop that provides the required goods. Scholars (Clark 1968) have found that 50-60% of the convenience goods are bought during shopping trips made to local centres. However, scholars (Pred 1967) have also observed that consumers tend to maximise the utility associated with shopping effort by combining multi-purpose trips, where within a single trip to the regionally accessible centre both convenience and specialised goods are purchased. Similar behaviour occurs when the consumer finds more and better quality goods at the regional centre, or during the trips that combine work with shopping, or with entertainment.

The next section looks at potential parallels between the geographical organisation of legal retail and illegal drug trading in the city.

7.3 Statistical analysis and results

The findings from the last two analysis chapters suggest that street drug dealing might be closely associated with the degree of movement permeability of street segments. In this chapter, drug dealing locations are further examined in relation to local and regional level of street permeability. In particular, the drug dealing locations of different types of drugs are examined in relation to street permeability; in order to test whether or not similar to low-value and high-value goods in legal retail, different classes of drugs might be sold at different spatially permeable locations in the city (see **Table 1**, hypotheses N1 and N2). For instance, it is expected that cocaine or heroin drug supply crime will be more associated with the regional than local scale of movement, and cannabis drug supply crime will tend to be located at the local scale of movement.

Furthermore, the quantity and variety of drugs sold per street segment is examined in relation to levels of street permeability. It is expected that more permeable locations will be associated with a larger variety and quantity of drugs traded, as these locations will attract more customers to the location (**Table 1**, hypothesis N3).

Finally, it is proposed that if there is a relationship between drug production and drug supply cases, than there should be a spatial dependency between where the drugs are produced, or large quantities of drugs are redistributed, and where the drugs are supplied (see **Table 1**, hypothesis N4).

The subsequent sections explore these propositions statistically.

Table 1: List of hypothesis to be tested in this chapter

N	Hypothesis
1.	It is expected that high value class drug dealing locations should be more clustered than low value class drug dealing locations across the street network.
2.	It is expected that the high order class drug dealing locations should be on street segments that are more spatially permeable than low order class drug dealing locations.

3. It is expected that those street segments on which there is more variety and a larger quantity of drugs being sold will be regionally permeable locations.
4. There is a spatial dependency between where drugs are produced and supplied.

7.3.1 The spatial hierarchical order of drug class types

In order to establish the spatial retail nature of drug markets, only drug supply cases are used in the following part of the analysis.

The *incident based street network* model described in Chapter 4 is used to test whether there are spatial regularities between where the different types of drugs are being sold and the permeability level of the street network. First, all drug types are classified into A, B and C categories (**Table 2**). Class A drugs are assumed to be the most harmful for the user and riskiest for the drug dealer, since for the possession or supply of A class drugs the highest punishment in UK can be received, i.e. life imprisonment. However, the supply of B or C class drugs can result in (up to) a 14 years sentence. Since the street price of A class drug is more expensive than B and C classes (Matrix Knowledge Group 2007), A class drugs are considered as 'high-rank goods' and B and C drug classes as ' low-rank goods'.

Due to the small sample size of class C drugs (2 incidents), the supply locations of this drug class are excluded from the current analysis and only the supply locations of A and B class drugs are examined. **Figure 1** illustrates the geographical distribution of drug supply crime for two types of drug commodities.

Table 2: Illegal drug classification (Police foundation 2000)

Drug class	Drug type
A	Cocaine, Crack, Heroin, MDMA, LSD, Methadone
B	Cannabis, Amphetamine
C	Ketamine

Given the differences in the street price of A and B drug classes and the associated legal punishments and risks involved for the drug dealers, it is proposed that A class drug dealing locations will have a different spatial distribution than the locations of B class drugs, see **Figure 1**. Mainly, it is anticipated that A class supply locations will be more clustered than B class supply locations. This proposition is based on the assumption that similar to legal trade, the most valuable goods will be clustered together and less expensive ones will have higher spatial dispersion. Since A class drugs are more expensive to purchase than B class drugs (Matrix Knowledge Group 2007), in the case of illegal trading, it is proposed that drug dealers that sell A class drugs will be located in close proximity of each other to benefit from the agglomeration affect of many potential customers attracted to the area (Rengert et al. 2005). This arrangement will also distribute the overall risk of being noticed or caught by the police among all the dealers (Weisburd and Green 1995). Apart from dissimilar geographical distributions of different classes of drugs, it is expected that a spatial hierarchical relationship between class A and class B drugs will be found, where the lower-class drugs are spatially dependent on higher-class drugs, but not vice versa. That is, drug dealers that sell mainly class B drugs are more likely to sell or be found near the dealers that sell drug A class, however the location choices of A class drug dealers will not depend on the locations of B class drugs.

Statistically, two methods of analysis are used to test these hypotheses: nearest neighbour (NN) test using street network distance and spatial regression analysis. Both methods were described in detail in chapters 3 and 5.

Figure 2 shows the observed and expected NN distance between drug supply points applied to two different samples of drug type class. It can be seen that in both cases the observed curve of real supply locations is above the simulated curve. Thus, both samples of locations are not randomly dispersed across the street network, but are spatially concentrated. Moreover, as expected drug supply A class is more clustered per street network length (up to 200 meter) than drug supply B class (up to 500 meter).

Furthermore, the juxtaposition of two drug class types are examined, where the NN index is calculated from all A and B class drug supply points correspondingly (see **Figure 3**). It can be seen that B class drug supply tends to cluster around A class supply locations, up to 100 meters away from A class. However, not necessarily vice versa, where A class drug supply crime is located up to 400 meter away from B type of drug crime supply. Thus, there is an asymmetric relationship between the clustering observed across drug classes.

Figure 1: A class (n=520) and B class (n=193) drug supply distribution in the borough aggregated to street segments

Drug supply A class	Drug supply B class

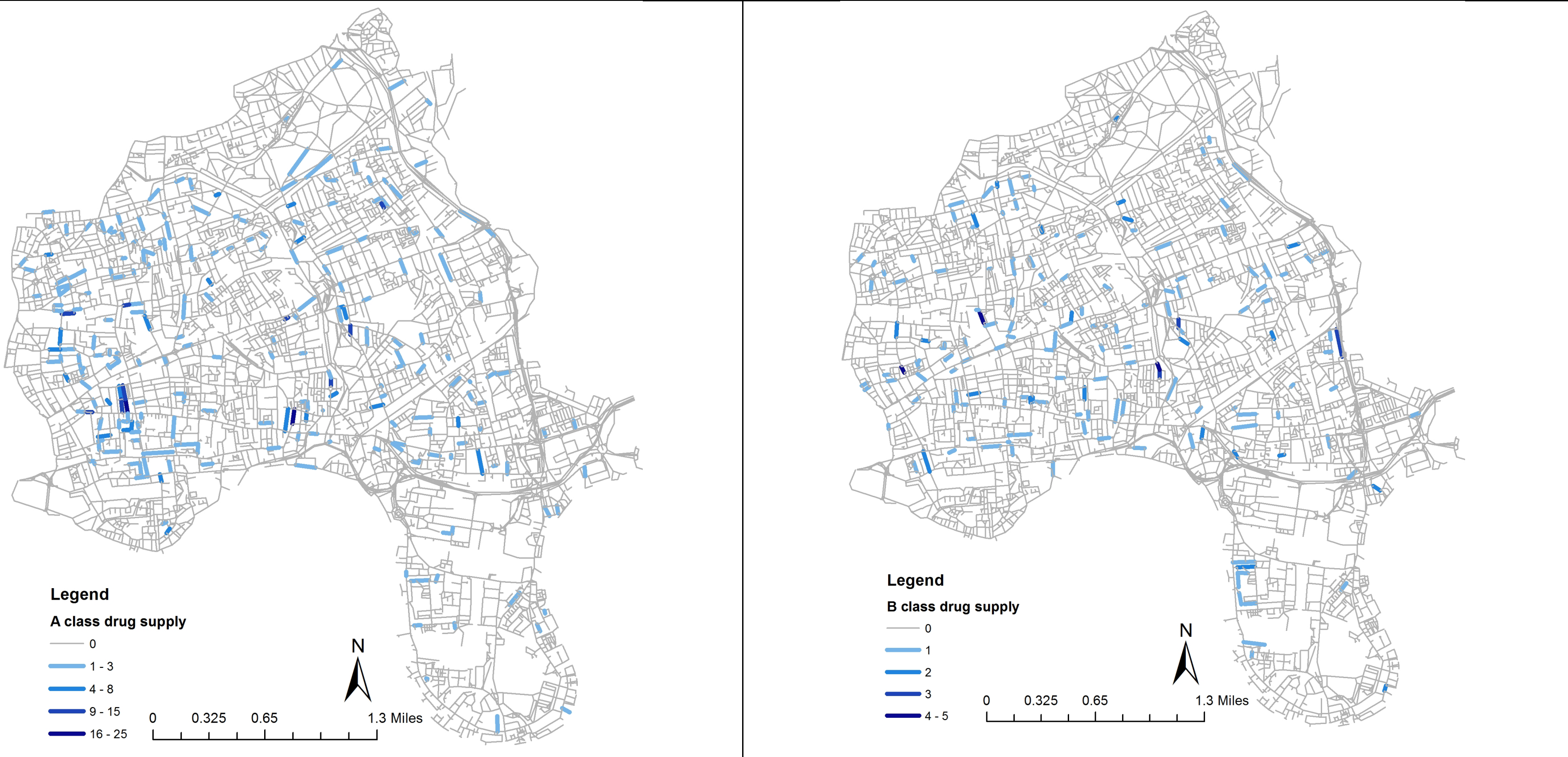


Figure 2: Observed and expected nearest neighbour curves for ***supply A class drugs*** and ***supply B class drugs*** calculated using shortest network distance

Drug supply A class | Drug supply B class

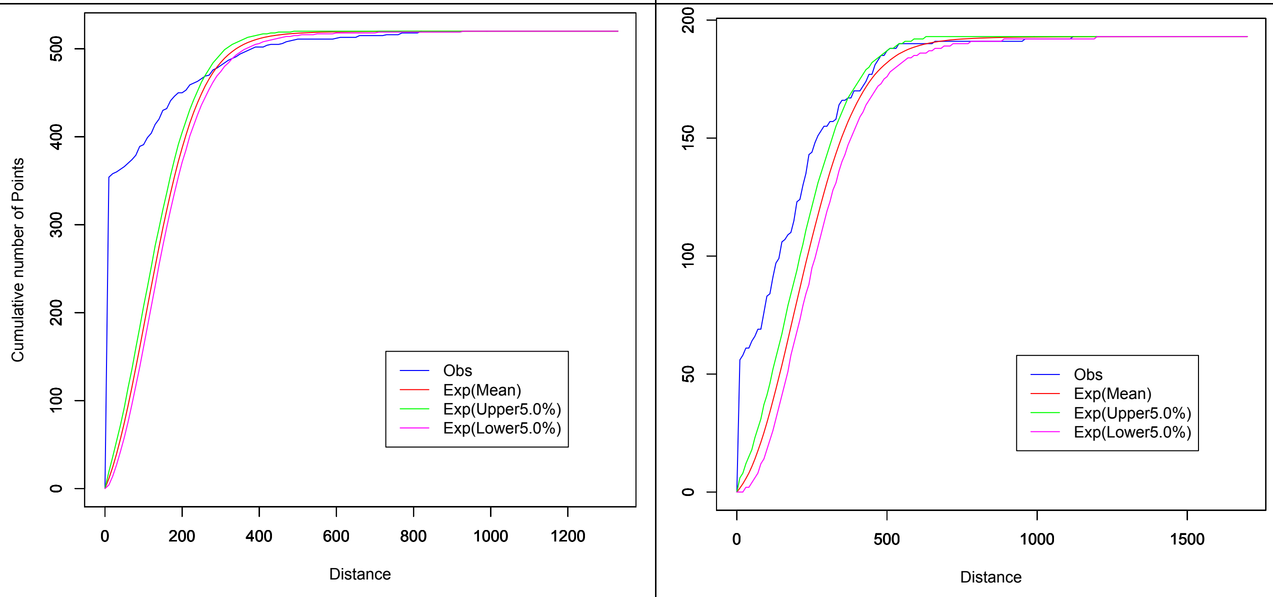
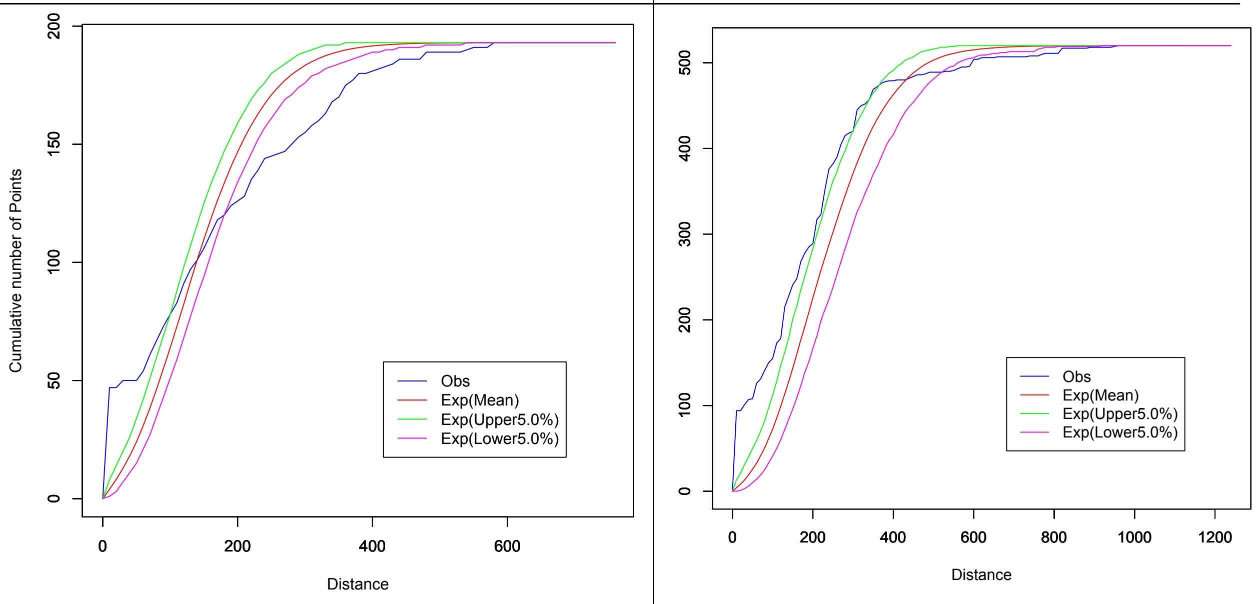


Figure 3: Observed and expected nearest neighbour curves for ***supply A class drugs to B class drugs*** and ***supply B class drugs to A class drugs*** calculated using shortest network distance

From A class supply to B class supply | From B class supply to A class supply



In what follows, the spatial differences between the two categories of drug supply locations are tested in relation to the degree of street permeability and several criminogenic land uses. It is expected to find that A class drug suppliers will be positioned on more regionally permeable locations where large scale movement passes by than B class suppliers due to the fact that A class drug commodities are more expensive.

It has been already stated that different land uses tend to be attracted to street segments with different levels of permeability. For instance, bars are likely to be located on segments that attract various categories of people that are both residents and visitors in the given neighbourhood. On the contrary, schools tend to be located on less permeable residential locations, where they can be accessible for children and youth living nearby. Thus, three types of land uses are selected as a proxy for capturing street level permeability and also being associated with drug supply crime. In Chapter 6 it was established that bars, schools and universities are associated with drug supply locations. Here, the same land uses with corresponding vicinities from 2.5 to 10 minutes walk are tested statistically for disaggregated drug supply locations according to drug class type. **Table 3** and **Table 4** show the results from the regression analyses.

It can be seen that 'A' class of drugs are more likely to be found on roads that are regionally permeable (Table 2) and 'B' class of drugs are more likely to be found both on the local and regional roads. Moreover, bars, schools and universities have a significant criminogenic affect on 'A' and 'B' class drug dealing up to 2.5 walking distance from the corresponding facility.

Table 3: Summary statistics for 4 separate models of Poisson-Gamma regression with **MCMC estimation method**, the dependent variable is **drug supply incidents class 'A'** incidents and unit of analysis is street segment (sample size n = 13,153 segments)

Summary of goodness of fit statistic	Model 1	2	3	4
Log likelihood	-1417.7	-1504.6	-1428.6	-1407.6
AIC	2980.1	3019.2	2865.2	2827.3
BIC/SC	3017.5	3056.6	2895.1	2872.2
Deviance	1235.7***	1161.5***	786.4***	808.5***
Pearson Chi-Square	11964.2	10144.0	11400.8	11693.1
Model error estimates				
Mean absolute deviation	0.14	6.59	0.54	0.26
Mean squared predicted error	0.09	74.01	251.81	63.81
Individual predictors	**Coefficients**			
Intercept	-7.43***	-6.38***	-4.98***	-5.39***
Segment length	0.02***	0.02***	0.02***	0.02***
Regional to movement (r4000)	0.96***	----	----	----
Local to movement (r800)	----	10.85 n.s	----	----
Regional through movement (r4000)	----	----	-0.00 n.s	----
2.5 min. walk from bar	----	----	----	0.59***
2.5 min. walk from school	----	----	----	0.38**
2.5 min walk from university	----	----	----	0.83***
Spatial autocorrelation	-0.00n.s	-0.00n.s	-0.00n.s	-0.00n.s

*** p<0.001, ** p<0.050

Table 4: Summary statistics for 4 separate models of Poisson-Gamma regression with **MCMC estimation method**, the dependent variable is **drug supply incidents class 'B'** incidents and unit of analysis is street segment (sample size n = 13,153 segments)

Summary of goodness of fit statistic	Model 1	Model 2	Model 3	Model 4
Log likelihood	-878.8	-875.1	-881.0	-858.7
AIC	1765.7	1758.2	1770.1	1729.4
BIC/SC	1795.7	1788.1	1800.0	1774.3
Deviance	687.1	685.6	678.4	719.1
Pearson Chi-Square	11078.0	10990.3	11098.0	11292.2
Model error estimates				
			0.04	0.03
Mean absolute deviation	0.03	0.03		
Mean squared predicted error	0.06	0.08	0.11	0.05
Individual predictors	Coefficients			
Intercept	-5.92***	-6.56***	-5.44***	-5.98***
Segment length	0.02***	0.02***	0.02***	0.02***
Local to movement (r800)	3.30 **	----	----	----
Regional to movement (r4000)	----	0.58***	----	----
Regional through movement (r4000)	----	----	$0.00^{n.s}$	----
2.5 min. walk from bar	----	----	----	0.57***
2.5 min. walk from school	----	----	----	0.71***
2.5 min walk from university	----	----	----	0.81**
Spatial autocorrelation	$-0.00^{n.s}$	$-0.00^{n.s}$	$-0.00^{n.s}$	$-0.00^{n.s}$

*** p<0.001, ** p<0.050

7.3.2 The quantity of drugs traded and permeability

In this section, the total frequency of drug events is compared with the local and regional level of street permeability. It is proposed that segments with *multiple incidents* of crime are more likely to be permeable locations than those with *one* or *no drug crime*. A multinomial regression is employed to test the relationship between categorically ordered groups of street segments, where the segments are classified as follows:

- '0' for street segments with no crime
- '1' segments with one drug crime of any category
- '2' segments with more than two drug crime of any category of drug (polydrug)

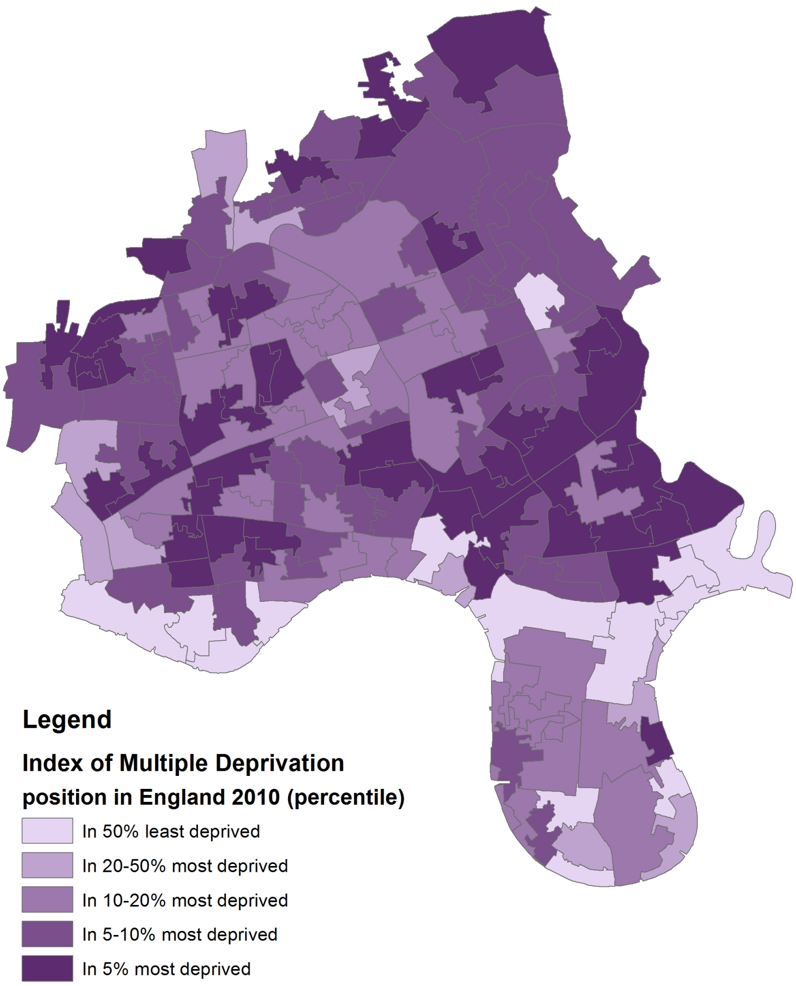
The model uses a set of independent variables to try to predict different likelihoods of a categorically ordered dependent variable. The independent variables used are as follows:

- high street (binary variable) - to indicate if a segment is on the high street
- near to the high street – to indicate if segments are one step away from the high street (binary variable)
- segment length (continuous variable)
- Index of Multiple Deprivation (IMD)(continuous variable measured at the areal level)

The high street variable is used as a proxy for identifying very permeable street segments in the neighbourhood. These are compared to segments that are one step away from high street, and those located further away. Street segment length is included to account for variation in street segment length. It is not possible to estimate the influence of spatial autocorrelation between the variables using a multinomial model, and so to capture the influence of factors that vary spatially, an area level variable is included. In this case, the Index of Multiple Deprivation is used to capture the areal level variation that cannot be explained by the model.

The IMD data was taken from official statistics (Crown copyright database). It is a combined index of 38 indices across the eight domains: income, employment, health, education, housing, environment and crime. **Figure 4** illustrates spatial variation in the IMD in comparison to the national percentiles at Layer Super Output Areas (LSOAs) level. It can be seen that deprivation is widespread in the borough: 72% of the borough falls into the 20% of most deprived category nationally and 40% of the borough is in the 10% of England's highest deprivation level and only 6% of Tower Hamlets is in the least deprived category.

Figure 4: The Index of Multiple Deprivation (IMD) for the year 2010, LSOA unit of analysis



The multinomial regression estimates k-1 models, where *k* is the number of outcomes. In this research segments with '0' drug crime are defined as the reference category in the model and these segments are compared to segments with one drug crime and more than two drug crimes. So, street segments with no crime are compared to segments with single and multiple incidents of drug crime. The multinomial logistic regression is defined as:

$$\Pr(y_i = j) = \frac{\exp(x_i \beta_j)}{\sum_j^J (x_i \beta_j)} \tag{7.1}$$

where $\Pr(y_i = j)$ is the likelihood of being a member of a group j, x_i is a vector of independent variables and β_j is the coefficient associated with variable *j* calculated using maximum likelihood estimation. **Table 5** and **Table 6** summarise the output from the regression model.

The Likelihood Ratio Test from the **Table 5** shows that the specified model is better than the null model; therefore the model explains some of the variance. This indicates that the given model might not fit the data well. However, this is due to the large sample size of the data. Three Pseudo R-square tests show the extent to which the model improves from the empty model. The Likelihood Ratio Tests, mainly Chi Square test shows whether or not the independent variables are significantly associated with the dependent variable. It can be seen that all variables are significant.

Table 5: Summary output of multinomial regression model, where the dependent variable is the drug supply crime and unit of analysis is street segment (sample size n=13,153 segments)

Model Fitting Information

Model	*Model Fitting Criteria* -2 Log Likelihood	*Likelihood Ratio Tests* Chi-Square	df	Sig.
Intercept Only	4882.763			
Final	4436.429	446.334	8	.000

Pseudo R-Square

Cox and Snell	.028
Nagelkerke	.105
McFadden	.091

Likelihood Ratio Tests

Effect	*Model Fitting Criteria* -2 Log Likelihood of Reduced Model	*Likelihood Ratio Tests* Chi-Square	df	Sig.
Intercept	4436.429[a]	.000	0	.
Index of Multiple Deprivation	4452.232	15.803	2	.000
Segment length	4766.489	330.060	2	.000
High street	4467.027	30.598	2	.000
One step off high street	4520.110	83.681	2	.000

Table 6: Summary output of multinomial regression model, where dependent variable is the drug supply crime and unit of analysis is street segment (sample size n = 13,153 segments)

Street segments with[a]		B	Std. Error	Wald	df	Sig.	Exponential (B)	95% Confidence Interval for Exponential (B) Lower Bound	Upper Bound
1 drug crime	Intercept	-5.448	.216	637.151	1	.000			
	Index of Multiple Deprivation	.015	.004	11.509	1	.001	1.015	1.006	1.024
	Segment Length	.013	.001	298.732	1	.000	1.013	1.012	1.015
	High street	.823	.214	14.758	1	.000	2.277	1.496	3.464
	One step off High street	.760	.128	35.176	1	.000	2.138	1.663	2.749
More than 2 drug crime	Intercept	-6.542	.333	385.262	1	.000			
	Index of Multiple Deprivation	.014	.007	4.433	1	.035	1.014	1.001	1.028
	Segment Length	.014	.001	159.314	1	.000	1.014	1.012	1.016
	High street	1.428	.283	25.432	1	.000	4.172	2.395	7.269
	One step off High street	1.385	.178	60.359	1	.000	3.996	2.818	5.668

a. The reference category is: 0, i.e. NO crime per street segment.

b. This parameter is set to zero because it is redundant.

Recall that the group of segments with no crime is used as a reference category to which segments with single and multiple incidents of drug crime are compared. Additionally, since two independent variables, high street and one step away from high street are binary coded, they have two categories, so *k* is *2*. According to *k-1* dummy rule, one category is left out in the model as a reference category and it appears equal to *0* in the table (see non high street segments and other street segments). So, the B coefficient shows how likely the high street segments compared to non high street segments will have one drug (or two or more) crime relative to no crime. In order to interpret the results from **Table 6** three cases of a coefficient need to be considered, bigger than zero, equal to zero and less than zero, see **Table 7.**

Table 7: Three cases of coefficient value for the 'high street' and 'one step away from high street' variables

High street coefficient (b)	Exponential coefficient (b)	Conclusion
>0	>1	High street segments compared to non-high street segments **are more** likely to have ***1 crime*** rather than NO crime
=0	=1	High street segments and non-high street segments **are equally likely** to have ***1 crime*** rather than NO crime
<0	<1	High street segments compared to non-high street segments **are less likely** to have ***1 crime*** rather than NO crime
One step away from High street coef. (b)	Exponential coefficient (b)	Conclusion
>0	>1	One step away from high street segments compared to other segments **are more** likely to have ***1 crime*** rather than NO crime
=0	=1	One step away from high street segments and other segments **are equally likely** to have ***1 crime*** rather than NO crime
<0	<1	One step away from high street segments compared to other segments **are less likely** to have ***1 crime*** than NO crime

The exponential 'B' indicates the odds ratio, for instance between high street segments and non-high street segments. Thus, the results from the **Table 6** can be interpreted as follows:

- When the odds ratio equals **2.277,** which is larger than **1**, the high street segments compared to non high street segments are 227% **more likely** to have **1** crime than NO crime incident.
- When the odds ratio equals **4.172,** which is larger than **1,** the high street segments compared to non high street segments are 417% are **more likely** to have **2** or more crime than NO crime incident.
- When the odds ratio equals **2.138,** which is larger than **1,** segments that are one step off high street compared to non high street segments are 213 % are **more likely** to have **1** crime than NO crime incident.
- When the odds ratio equals **3.996,** which is larger than **1,** segments that are one step off high street compared to non high street segments are 399% are **more likely** to have **2** or more crime than NO crime incident.

It should be noted that all of the results are statistically significant. Thus, it appears that overall, the high street segments have a higher chance of being targeted for drug dealing than non-high street segments. Moreover, segments that are one step away from the high street have also a higher likelihood of multiple incidents of drug crime. Segments that are one step away from high street are more significantly probable to have more than two drug crime than one drug crime.

7.3.3 The variety of drugs traded and permeability

In the previous section the quantity of drug supply crime was examined in relation to one measure of permeability at the street level. In this section, the quantity and variety of drugs being sold per street segment is compared to street level permeability. In order to calculate the combined index of quantity and the variety of illegal drugs being supplied per street segment, Simpsons Reciprocal index of diversity (Simpson 1949) is used. The index is commonly used to quantify the biodiversity of an ecological area, where the number and abundance of species is counted. It consists of two main variables termed *richness* and *evenness*. In this research, the index of richness gives an understanding of how many drug class categories are being sold per street segment. The more classes present per segment, the' richer' the given segment can be considered in terms of the drugs being sold at the given location. Evenness is defined as a degree of relative quantity of the different drug categories being supplied per given segment. Thus, the Simpsons index is defined as:

$$D = \frac{\sum n(n-1)}{N(N-1)} \qquad (7.2)$$

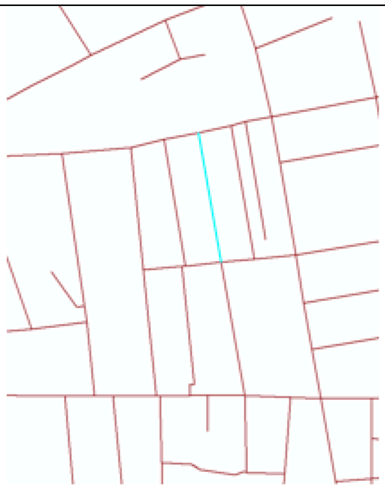
where n is the total number of drugs of a particular class and N is the total number of drugs of all categories. Simpson's index is calculated for every street segment in the area and ranges from '0' infinite diversity to '1' no diversity. This is counterintuitive, since larger values have less diversity. The reciprocal of the index is derived (1/D), where '1' denotes for the lowest diversity value and higher values indicate the greater variety of drugs being sold per street segment. Street segments that have no crime will have 0 diversity value. And the street segments where only two categories of drugs are sold will be considered less diverse than a street segment where three or more drug categories are sold in similar quantities. It can be suggested that as more quantity and variety of drugs are sold per segment, the more is the likelihood that the given street segment is a drug marketplace.

From the police dataset it is evident that nine different types of illegal drugs were sold in the case study area. Table 8 lists all nine categories with the corresponding sample size of drug types. Table 9 shows an example of how the index was calculated for every street segment in the case study area.

Table 8: Drugs present in the case study area with corresponding sample size

N	Illegal drug name (n)	N	Illegal drug name (n)
1	Cocaine (190)	6	Methadone (9)
2	Crack (107)	7	Cannabis (193)
3	Heroin (211)	8	Amphetamine (1)
4	MDMA (10)	9	Ketamine (2)
5	LSD (5)		

Table 9: The quantification of the Diversity Index for a single street segment

Street segment location	Drug category	Number (n)	n(n-1)
	Cocaine	1	0
	Crack	5	20
	Heroin	7	42
	MDMA	0	0
	LSD	0	0
	Methadone	0	0
	Cannabis	5	20
	Amphetamine	0	0
	Ketamine	0	0
	Total (N)	**18**	**82**

$$D = \frac{82}{18(17)} = 0.27$$

$$Simpson's\ Reciprocal\ Index = \frac{1}{D} = 3.7$$

If people deal randomly, more diversity would be expected at locations that are more permeable, since more transactions will happen per time unit given the large number of potential customers passing by. In order to test whether or not there is an association between street permeability level and high diversity index, the Poisson-

Gamma regression is employed. Here the dependent variable is the diversity index[1] per street segment and the explanatory variables are segment length and to-movement and though-movement permeability at different spatial scales (**Table 10**). The test of skewness in the dependent variable is significant and highly skewed: the ratio of simple variance to mean is 7:1 indicating over-dispersion in the dependent variable (**Table 11**).

Table 10: Descriptive summary of all the variables used in the regression (n = 13,153)

		Variable	Mean	Standard deviation	Min. value	Max. value
1.	Dependent	Diversity Index for supply crime count[1]	0.16	2.81	0.00	100.00
1.	Predictive	Segment length	39.42	40.67	1.00	400.30
2.		To-movement permeability (r800m)	0.15	0.05	0.02	0.36
3.		To-movement permeability r4000m)	1.91	0.55	0.46	3.42
4.		Through-movement permeability (r400m)	644.26	1640.88	0.00	13476.00

Table 11: Summary of diagnostic tests for dependent variable (n = 13,153)

N	Test name and estimation parameter		*Estimated value*
1.	**Test of skewness**	G	44.93***
		SES	0.02
		z	2286.85
2.	**Ratio of variation to mean**		7.40
3.	**Moran's I** (*p<0.05)		0.002*

[1] The values were rounded to integer values, by multiplying the diversity index by 100

A test of autocorrelation in the dependent variable showed that the diversity index is spatially dependent: Moran's I value (I=0.002, $p<.05$). The Moran correlogram with simulated 95% confidence intervals showed that in comparison to theoretical random autocorrelation, the observed value of dependent variable of nearby segments is significantly and positively autocorrelated with a sharp decrease in distance over the large scale, up to 1 mile (1.6km) (see **Figure 5**). Based on this the model parameters for modelling autocorrelation are chosen with the search distance up to 1 mile (1.6 km), after this distance the weight equals 0, and the α equals -35.503591 (refer to Chapter 5, section 4 for detailed explanation on parameter selection procedure).

Figure 5: Moran's I value (blue) plotted along with 2.5 (red) and 97.5 (green) simulated percentiles against the distance intervals, for the Simpson's diversity index. The sample size is n=13,153 segments and the number of iterations is n= 100.

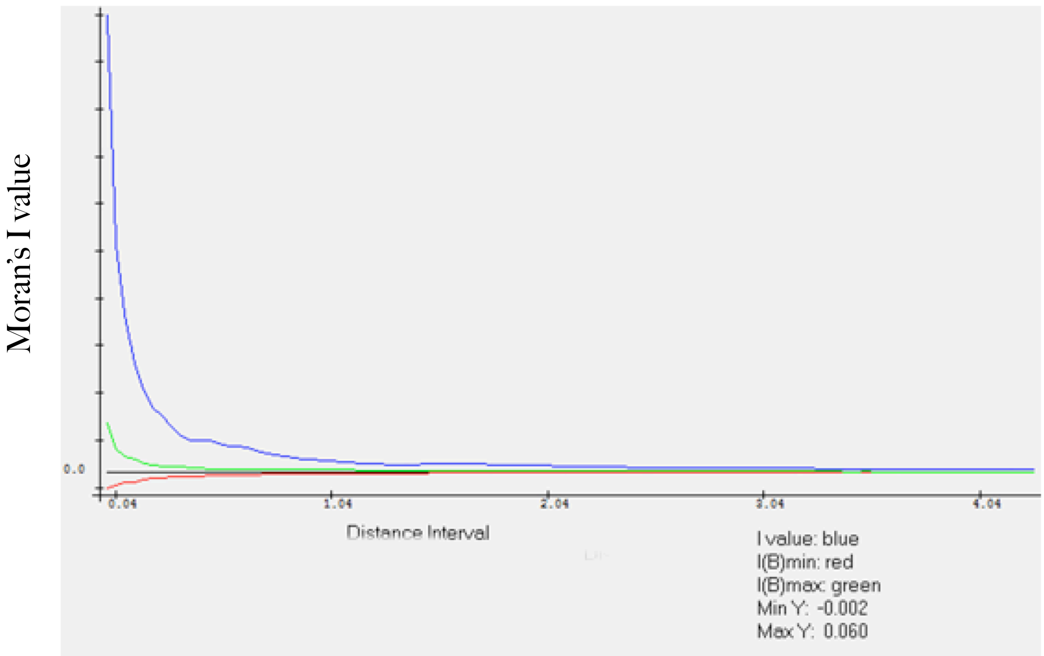


Table 12 shows the results from the regression analysis. It can be seen that the diversity index is significantly associated with destinations that are regionally very permeable, and not necessarily used for regional through movement. Thus, it can be proposed that high diversity segments that potentially can be classified as drug markets are located on street segments that are regionally very well connected, but not necessarily located on high through-movement segments that are away from streets with a high number of potential guardians passing by.

Table 12: Summary statistics for 4 separate models of Poisson-Gamma regression with MCMC estimation method, the dependent variable is **Simpson's diversity Index** and unit of analysis is street segment (sample size n=13,153 segments)

Summary of goodness of fit statistic	Model 1	Model 2	Model 3	Model 4
Log likelihood	-756.8	-759.8	-760.4	-751.8
AIC	1521.7	1527.6	1528.9	1515.7
BIC/SC	1552.3	1558.2	1559.5	1561.6
Deviance	158.4 ***	157.6 ***	157.3***	158.5***
Pearson Chi-Square	14789.2	10977.6	11700.3	21763.3
Model error estimates				
Mean absolute deviation	0.39	0.89	1.90	3.00
Mean squared predicted error	165.18	922.97	5054.95	2479.43
Individual predictors	**Coefficients**			
Intercept	-8.40 ***	-5.58***	-4.70 ***	-7.07***
Segment length	0.04***	0.04***	0.04***	0.04***
Regional to movement (r4000)	1.88 ***	----	----	----
Local to movement (r800)	----	6.54 n.s	----	----
Regional through movement (r4000)	----	----	-0.00 n.s	----
2.5 min. walk from bar	----	----	----	0.49 n.s
2.5 min. walk from school	----	----	----	1.36**
10 min walk from hospital	----	----	----	1.67**
Spatial autocorrelation	-0.00 n.s	-0.00 n.s	-0.00 n.s	-0.00 n.s

*** p<0.001, ** p<0.050

7.3.4 The spatial dependency between drug supply and drug production cases

So far, only drug supply cases have been examined in relation to spatial variables. However, if it is possible to derive a business model of street level drug marketplace, it is plausible to assume that drug supply and drug production locations might be spatially related in order to facilitate the production-supply chain. **Figure 6** shows the point pattern for incidents of drug supply and production. It should be noted that the drug production category includes the large-scale distribution of drugs (drug production locations are indoor locations). Prior research (Eck 1995; Rengert et al. 2000) does not suggest that these two drug crime categories are related; however if they are, we would expect to find multiple locations of drug supply near to drug production location (s).

Figure 6: Location of drug production crime within 2.5, 5 and 10 minutes walking distance and the location of drug supply

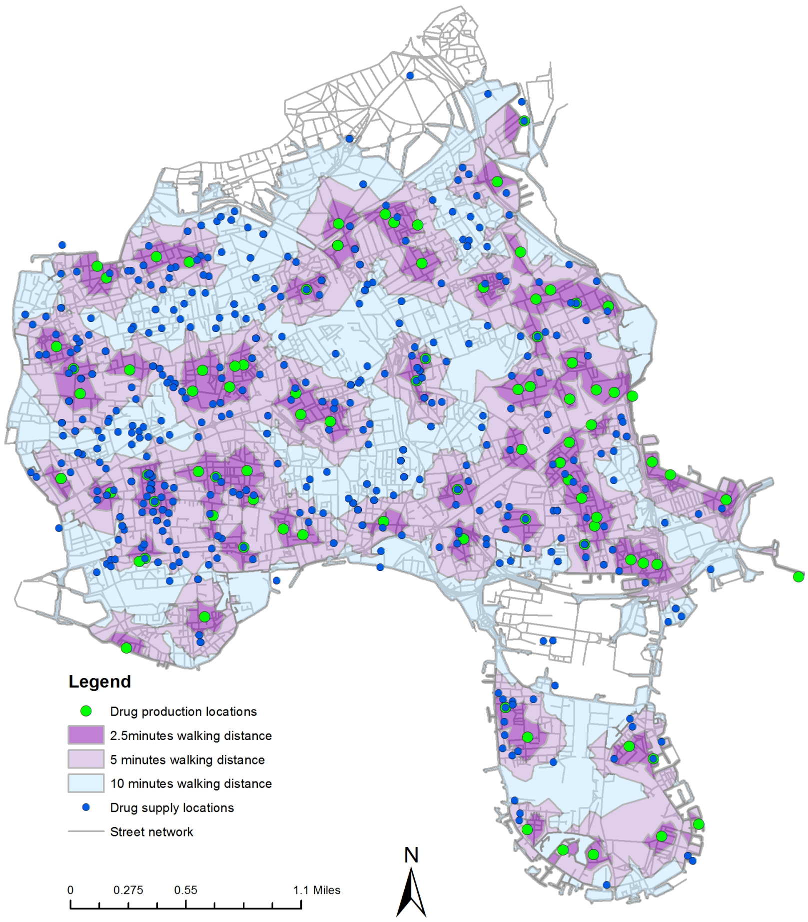


Table 13 provides descriptive statistics regarding the density of drug supply locations within 2.5, 5 and 10 minutes walking distance of drug production crime. These frequencies are compared to those expected, assuming that there is no particular pattern. The expected count is calculated by multiplying the total number of observed drug supply crime (i.e. 732) by the street network length of the corresponding buffer (i.e. 135km for the buffer from 0 to 2.5 minute walk) and divided by the total length of the street network (953 km). Thus, equal proportions of expected drug supply crime are derived for each buffer. Further, the expected density of drug crime is calculated by dividing the number of crime proportions to segment length.

It can be seen that in comparison to the expected distribution of drug supply crime, the observed distribution is more clustered within 2.5 minutes walking distance than within 5 or 10 minutes walk. **Table 14** shows this result statistically using a regression model. It can be seen that there is a significant relationship, where the drug supply locations are distributed within 2.5 minutes walking distance from production locations.

Table 13: Supply crime count on segments that are 2.5, 5 and 10 minutes walk from drug production location (2.5, 5 and 10 minute walking equals to 200m, 400m and 800m distance for London area correspondingly)

Segment with drug production location	Supply crime **count**				Segment **length (km)**				**Density** of supply crime			
	Walking distance measured according to time in minutes											
	0-2.5	*2.5-5*	*5-10*	*Elsewhere*	*0-2.5*	*2.5-5*	*5-10*	*Elsewhere*	*0-2.5*	*2.5-5*	*5-10*	*Elsewhere*
Observed count	253	247	217	15	135	257	219	342	1.87	0.96	0.99	0.04
Expected count	104	197	168	262	135	257	219	342	0.77	0.76	0.76	0.76

Table 14: Summary statistics for 3 separate models of Poisson-Gamma regression with **MCMC estimation method**, the dependent variable is the number of **drug supply** incidents and the unit of analysis is the street segment (sample size n=13,153 segments)

Summary of goodness of fit statistic	Model 1	Model 2	Model 3
Log likelihood	-1972.0	-1973.3	-1973.6
AIC	3952.1	3954.6	3955.2
BIC/SC	3982.1	3984.5	3985.1
Deviance	1203.0***	1198.7***	1197.4***
Pearson Chi-Square	18761.0	17839.8	18054.7
Model error estimates			
			0.6
Mean absolute deviation	0.5	0.5	
Mean squared predicted error	224.7	250.7	286.1
Individual predictors	**Coefficients**		
Intercept	-4.68***	-4.58***	-4.65***
Segment length	0.02***	0.02***	0.02***
2.5min walk from drug production point	0.30***	----	----
5 min. walk from drug production point	----	-0.12 n.s	----
10 min. walk from drug production point	----	----	0.05 n.s
Spatial autocorrelation	-0.00 n.s	-0.00 n.s	-0.00 n.s

*** p<0.001, ** p<0.050

7.4 Discussion

The preceding two chapters demonstrated a significant association between street network permeability and the occurrence of drug crime. The aim of this chapter was to examine whether or not the degree of street permeability can further uncover the potential locations of drug marketplaces and whether or not the markets can be classified in terms of the type of drugs being traded on streets segments and by their juxtaposition in the neighbourhood. Despite the wide-ranging research on the street drug markets (Parker and Newcombe 1987; Bennett and Sibbitt, 2000; Curtis and Wendel 2000; Cyster and Rowe 2006, Wilson et al. 2002), little is known about how the drug dealing locations that potentially form drug marketplaces relate to each other geographically. In this chapter the spatial juxtaposition of different types of drugs traded across the street network was examined explicitly. The general findings are summarised below.

Two spatial regularities were identified in the location preferences of drug dealing across the street network. Mainly, the dealing locations of class A drugs were significantly associated with streets that are permeable as a destination at the regional scale of movement. The locations of class B drugs were significantly associated with locations that are locally permeable, but also with locations that are regionally permeable. Furthermore, it was observed that class A drugs were clustered next to each other but class B drugs were more dispersed. Similarly, there was an asymmetric spatial relationship between A class and B class drugs, where B class drugs were clustered near A class drugs, however not vice versa. Based on these observations, it is suggested that illicit drugs might share some characteristics of legal retail markets, where high-value (Class A) drug dealing is more likely to be found at very permeable locations in the city that attract many potential customers, and lower-value (Class B) drug dealing is more dispersed at local neighbourhood scales. However, low-value class drug dealing tends to be positioned near to high-order class drugs, which suggest that this positioning allows dealers to benefit from the agglomeration of many customers attracted to the area. The index of diversity that estimates the quantity and variety of different drugs sold per street segments supports these propositions. The index was significantly associated only with regionally permeable locations, indicating that segments that are associated with the citywide scale of movement have more variety in illicit drug dealing than those that are less permeable or are permeable at local scale of movement. It is proposed that these regionally permeable streets are more likely to be the locations of drug marketplaces.

It should be also considered that both classes of drugs were only significantly associated with locations that are permeable as local and regional destinations, but not with the permeable streets that are used to move-through and between activity centres in the city. Thus, both classes of drugs are only associated with those locations that do not have guardianship in the form of transitory movement that will detect or prevent the drug transaction.

In order to supply these marketplaces with drugs, it is proposed that these locations might also attract drug production incidents, since a significant association was found between the locations of supply and production. That is, drug dealing locations were concentrated at locations within 2.5 minutes away from drug production locations.

Similar to the results from Chapter 6, both drug class types were also significantly associated with criminogenic land uses. In particular, a positive association was found with locations that are 2.5 minutes away from bars, schools and universities.

To conclude, these results support the proposition (Eck 1995) that there are (economic) similarities between drug markets and their legal counterparts. That is, for the current sample of data at least, both illegal and legal retail share a similar spatial nature in the way different classes of goods are distributed across the street network. It is proposed that the location of illicit drug retail is shaped by the spatial characteristics of urban settings to deploy the supply of illicit drugs to the potential consumers.

CHAPTER 8:

Discussion and conclusion

Introduction

The focus of this research was to examine drug crime in relation to spatial patterns of urban fabric. In comparison to previous studies (Rengert et al. 2005; McCord and Ratcliffe 2007), in this research drug crime incidents were explicitly examined at the street-scale of resolution using a street network matrix including street network distance buffers. The empirical analysis was based on a novel combination of environmental criminology and urban theories. These include Routine Activity Theory, Crime Pattern Theory and Configurational analysis of the street network. The research explored the spatial-topological characteristics of drug crime in the city. The research also explicitly disaggregated drug crime incidents into drug supply, drug possession and drug production cases and examined their spatial patterns separately. This gave a valuable insight into the geography of different types of drug crime. In particular, patterns of drug crime were examined statistically with respect to three features of the urban fabric that potentially influence drug crime location choice. These are the street network, movement dynamics and land use distribution. Consequently, a novel methodology was used where different definitions of street permeability were examined, within a single study in relation to drug crime. Similarly a new approach was used to examine the degree of street permeability in conjunction with criminogenic land uses within a single study.

The final chapter of this research discusses and synthesises all the major empirical findings. First, the main objectives of the research are revisited, followed by a discussion of significant empirical findings. Next, the theoretical implications and significance of these findings are discussed. Some limitations of the study are also considered. The chapter ends with the discussion of potential future work.

8.1 Main objectives and empirical findings

The research was structured around three main objectives. First, to examine where drug markets are located in the city, primarily to investigate the influence of the urban street network configuration on individual incidents of drug crime placement. Second, to ask why these places are attractive for illegal trading, and in particular, to examine the extent to which drug crime is related to, or spatially embedded within the spatial distribution of legal land uses. Third, to examine why drug dealing incidents are spatially arranged as they are, by exploring the spatial juxtaposition of clusters of drug crime incidents in relation to each other and the spatial characteristics of the street network.

It was assumed that the likelihood of drug crime occurring on a given street depends on the daily routine patterns of drug dealers and drug users, and that drug transactions are likely to occur at certain locations at some time intervals, if capable guardians are absent or cannot prevent the drug transaction. From the offender's perspective, it was assumed that dealing site selection involves multistage decision-making process, whereby visiting different places during routine activities across the city, offenders pass through and identify routes that have less capable guardians, and might be potentially attractive drug dealing sites.

From this perspective, there are several major findings from the research. First, an extensive statistical analysis of movement flows and the geometry of the street layout showed that the locational choices of drug crime follow distinct spatial patterns. For example, the probability of drug crime occurring on a street segment is not random and it is influenced by the relative positioning of a segment in the configuration of street network. This is consistent with the suggestion that drug dealers make (bounded) rational choices as to where to offend. Mainly, drug crime tends to happen on segments that feature similar levels of permeability to pedestrian movement. In line with previous research conducted on the North American street grid (Eck 1994), for the European street grid considered here a clear association was found between drug crime locations and permeable roads, particularly those that are permeable as a destination at the regional intra-city scale of movement. One interpretation of this is that for a drug dealer those segments appear to be considered to offer good retail potential that attract a large amount of both locals and visitors coming to the area.

It should be noted that no relationship was found for permeable roads that are used for through movement between locations, only those segments that are reached with less effort from all other segments in the city were associated with drug crime. The drug dealing destination preferences at the regional scale of movement suggest that the street network supports opportunities for regional drug markets to be established at the locations that are permeable for many people to visit frequently and with little effort. One such location in the network is the high street. It was found that high streets and the segments that were one turning away from these were associated with an elevated level of drug crime. It was suggested that by attracting large movement flows, the active retail street boosts the risk of drug crime not only for the high street itself, but also for the segments that are leading to and from these permeable streets. Importantly, given the illegal nature of the drug transaction, the streets that are one turning away from high street offer to a drug dealer an acceptable balance between their accessibility to many potential clients, and relatively acceptable levels of guardianship that reduce the risk of legal prosecution. This finding supports the proposition (Eck 1995) that greatest utility locations for drug dealers are those where the potential sales do not outweigh the associated risk of being detected.

Furthermore, depending on the nature of the drug crime considered, in this research categorised as drug production, drug supply and drug possession, the locational choices of crime varied. As mentioned above, the drug supply offences were associated only with regionally permeable destinations. Drug possession crime was found at many places across the network, including both very locally and regionally permeable locations. Although stronger associations were found with locally permeable locations, suggesting that the drug possession might be more associated with local neighbourhoods than intra-city scale destinations.

With drug production cases, although it was hypothesised that this type of drug crime would be associated with less permeable locations, no statistical support was found for this proposition. On the contrary, similar to other types of drugs, drug production locations were positively and significantly associated with permeable streets, such as high streets. Moreover, there was a significant geographical relationship between drug supply and drug production locations. In particular, it was found that the locations of drug production incidents where located in close proximity to drug supply locations. Based on this, it is reasonable to assume that there might be a drug production - supply chain that distributes the illegal commodities across the locations. Thus, if one drug production location is closed down, it may reduce both the drug supply instances in the area and the supply locations as well.

Second, after accounting for the street network effect on drug crime occurrences, an extensive statistical analysis of legal land uses showed that the drug crime locational choices are additionally influenced by the presence of legal facilities in near vicinity. Although these are legitimate facilities, due to their specific characteristics and the way people's routine activities are centred around them, it may be that they indirectly have a criminogenic influence on the segments that were located in close proximity of those facilities. Thus, in addition to permeable locations, drug dealers prefer locations that are close to certain facilities or urban activities that attract many more potential customers to the area.

The criminogenic field from certain types of land uses was examined in relation to drug crime, particularly how far from a facility illegal activity was distributed along the network. A significant criminogenic association was found between street segments with drug crime and certain facilities, mainly drinking establishments, transport stations, money-lending shops, educational, healthcare and recreational land uses. The criminogenic influence was not similar for all these facilities and it also varied by the type of drug crime.

A significant criminogenic effect was found between segments that were located in close proximity to drinking establishments. Specifically, segments are more likely to have drug supply or drug possession cases if they are located in very near vicinity of these facilities (up to 2.5 minutes walk) than somewhere else. Importantly, only those segments that were located near to both drinking establishments and a high street had a risk of drug crime offences. Those segments that were located near to drinking establishments but far from high street were not significant. Thus, depending on the location in the network in relation to the high street, two facilities of the same type had a different risk of drug crime. Notably, when the facility was located closer to the high street, the latter had an added effect on the likelihood of drug crime.

Furthermore, segments located near to tube stations had different crime risks depending on the type of drug crime considered. Drug supply cases were highly likely not to be in close vicinity to the facility, but within a couple of street turnings away (from 2.5 minute to 5 minute walking distance from the tube). In contrast, drug production cases tended to concentrate in the immediate vicinity of the facility.

Similarly, drug supply and possession cases were concentrated in very close vicinity to money lending shops. The segments comprising the university campus also had an elevated risk of drug supply and possession crime, up to a 5-minute walk from the facility. Likewise, the segments that were from 2.5 and 10 minutes walking distance away from the hospitals were associated with drug supply and drug possession crime correspondingly. Importantly, only those segments near the university that were also located near the high streets had an elevated risk of drug crime.

A different pattern was observed with schools. The segments that were leading to and from these facilities (up to 5 minutes walking distance) had a high likelihood of drug production, supply and possession offences. Notably, the schools that were located close to high street and away from high street, in the interstices of the neighbourhood, had a criminogenic effect on the segment leading to and from the facility. However, the risk of drug crime was considerably higher for those segments that were located close to both a school and a high street. Thus, the high street has an additive effect.

The 'land use - drug crime' results are in line with Crime Pattern Theory, suggesting that legal facilities have an effect on crime, moreover a specific criminogenic field of every facility can be identified. Additionally, the results are in line with the 'risky facilities' proposition (Eck 2007), where a facility of the same type can have different risks of crime depending on the positioning on the network, and in relation to permeable streets.

Finally, after accounting for street network and land use effects on occurrences of drug crime, statistical analysis of different types of drugs sold across street network was examined. The analysis showed that there might be a specific spatial pattern in the way the different drug types were traded in the city. Mainly, A class drug dealing, such as cocaine, crack and heroin were more clustered near regionally permeable streets that potentially attract both local and regional customers; and low-order class drug dealing, such as cannabis and amphetamine were more dispersed in the local neighbourhood. Although, the low order class drugs were located near high order drugs, the latter were less likely to be located near low order class. Hence, there was an asymmetric spatial pattern in drug dealing. The estimate of the quantity and variety of different drugs sold per street segments, further suggests that more illicit drug variety will be found on those segments that are permeable at citywide scale than local scale. These segments potentially might comprise a drug marketplace.

Overall, the results suggest that at the subconscious level drug dealers actively engage and read spatial information, in order to make rational choices regarding the location of future transactions. Moreover, these choices are spatially bounded to both specific patterns of street connections and the economic utility of urban street network itself.

These findings raise the possibility that drug crime concentration in the city, particularly along the street network, has less to do with social disorganisation (Shaw and McKay; 1942) leading to weak social resistance to the drug market's existence in the area, but more to do with how the layout of the street network impacts upon the specific activities of urban dwellers, and the extent to which they *can* act as guardians against crime. That is, the topology of the street network may affect the potential for residents or passers-by to observe criminal activity, or to act as a deterrent that prevents it. Such a topological explanation, which contrasts with the social underpinnings of social disorganisation theory, could be an important development that could facilitate further research in the field of criminology and urban studies.

8.2 Towards the spatial rationale of drug markets

Based on the major findings, several propositions are made regarding the spatial nature of drug markets.

One of the models proposed by Eck (1994) to overcome the access-security dilemma was the *routine activity model*, where drug transaction happens near places that are used routinely by potential buyers and dealers. Reuter and MacCoun (1993) further suggest a typology of open drug markets based on whether or not most of the buyers and dealers live in the same locale or visit the area – *local*, *export*, *import and public* drug markets. Describing the spatial dimension of the locations that were associated with drug crime can further advance this typology.

First, the drug markets could be categorised topologically in relation to the main movement flows in the city: *regional* and *local* drug markets. Regional drug markets are more likely to be established at those locations in the city that attract potential users from local neighbourhood to citywide catchment area. Local street drug markets are more likely to be positioned at the locations that are easily accessed from local neighbourhoods. Moreover, with regional street drug markets, higher class and greater diversity of polydrugs are more likely to be sold per street segment. This market will be more clustered near to the regionally permeable location. With local drug markets, only the lower class of drugs is likely to be supplied. These drug dealing sites are more likely to be dispersed in the neighbourhood in comparison to regional markets.

Given that drug crime was also strongly associated with the proximity to some legal facilities, the markets could be further grouped according to the routine activities of the places of attraction. For example, recreational drug markets that are located at segments that have night-time entertainment economy of large number of bars and clubs clustered together. Here the drug crime is more likely to involve the dealing of recreational drugs to groups of people that were attracted to the area for entertainment purpose. These markets are more likely to be regional drug markets as well, since in order to sustain the night-time economy the legal facilities are located on regionally permeable locations that will attract large numbers of users.

The drug markets may also be grouped according to public transport and educational routine activates. The transit drug markets will most likely to be located near regional transport interchanges, where several transport nodes intersect. The rapid access and escape routes that this type of facility provides might be very attractive not only for the drug supply, but also for drug production or distribution of large quantities of drugs. Thus, a drug market may prosper in close proximity to this type of facility.

With educational activities, two types of facilities were identified – universities and schools. Those universities that are located near high street, most probably will be prone to drug crime. Thus, a local drug market may be established near the campus. Similarly, with schools those that were located closer to the high street are more likely to have drugs supplied on the segments leading to/from the school.

The proposition presented above regarding the potential locations of the drug markets, indirectly suggests that at the subconscious level drug dealers actively engage and read spatial information, in order to make rational choices regarding the location of future transactions. Moreover, these choices are spatially bounded to both specific patterns of street connections, routine activity of places and the economic utility of the urban street network itself.

8.3 Methodological developments

Given the multidisciplinary nature of this research, several methodological improvements were developed in this research that may potentially enhance the future research on crime in both disciplines.

Previous studies of drug crime have examined the spatial distribution of events using 'classical' Euclidean space as the metric of choice, without reference to the composition of the street network. Although targeting clusters of crime has proved to be an effective crime prevention measure (Weisburd and Green 1995), it is argued (Hillier and Shu 2000) that by looking only at geographical pockets of crime the police may fail to identify general patterns (type of roads, spatial settings, proximity to specific locations) that are common across the urban fabric and usually are not confined to one location. These patterns may be based on shared spatial geometry and topology of the street network, thus they cannot be identified from data cluster analysis.

In contrast, in this study the structure of the street network was explicitly examined to see if and how patterns of drug crime are associated with it. In order to capture the spatial nature of street drug dealing, the street segment was adopted as a unit of analysis. The street network analysis technique was used to spatially map and analyse drug incidents. This type of linear mapping represents finer grain analysis, where the incident map shows the crime concentration along the existing street network. In comparison to ward or LSOA units of analysis, where the case study area is defined as polygons that contain crime incidents, the segment unit of analysis closely replicates the street grid and contains crime incidents that are on or near to the given segment. Thus, the approach facilitates both the spatial precision in the modelling of the urban layout, and the ability to compare places with common spatial properties that aren't identifiable readily from a different type of map.

It should be noted that as with any unit of aggregation, the segment unit has also a potential size problem, where a significant variation of crime rates was directly related to the variations in segment length. Thus, two segments with equal crime counts might have different crime rates, because their lengths were dissimilar. Thus, a shorter segment might appear to have more crime than a longer one. In order to overcome the dramatic variations of segment length, in this study the length was included as a separate independent variable into the regression model. Hence, this showed the amount of opportunity for drug crime per meter segment length.

Using the segment as a unit of analysis allowed the development of an additional method to examine land uses in relation to drug crime. That is, street network distance buffers were used (instead of Euclidean metric) to test the criminogenic effect from the facility. The buffers were defined according to distance and time metrics, where time was used as a proxy of the distance travelled from the facility. This method not only brought more precision in examining only those street segments that were directly accessible to/from the land uses, but it also allowed for analysis to be carried out that identified the potential criminogenic field of the facility across the street network.

Furthermore, the street network matrix was used to calculate topologically derived permeability measures. It was shown that permeability is not an administratively defined measure of the amount of movement passing by the road, but it is a direct outcome of the configuration of the street network. And in order to use this measure in the analysis of crime, it should be calculated using a topologically defined street network matrix.

Finally, like any geographical data, the street segments are interrelated and statistically dependent. Thus, the research has accounted for spatial autocorrelation in the crime observations, where an autocorrelation parameter was included into the regression that accounted for size and nature of segments neighbouring effect. This allowed the identification of those variables that are 'truly' significant and that partially explain the great variation in drug crime counts from segment to segment in the city.

8.4 Practical application

Since the study is conducted using data for a European style of street network and the findings are in line with earlier research (Eck 1995; Rengert et al. 2005) conducted in North American cities, it is expected that the research will be interesting to both a UK and an international audience. For instance, the knowledge regarding the type of roads that are more prone to drug crime and legal facilities that have higher likelihood of drug crime in near vicinity could inform police crime prevention strategies. Moreover, the knowledge regarding criminogenic facilities may help to develop crime prevention initiatives in collaboration with the managers of those facilities (Eck 1996; Madensen and Eck; 2014). The findings may also inform urban schemes that are directed at long-term strategies to support neighbourhoods and local businesses, where the resources may be allocated with the consideration of the effect that the drug crime has on legal activities in the city.

Thus, the main objective of the practical application of the thesis is to communicate with end-users from private and public sectors in the best ways, by tailoring the thesis material to suit their needs[1]. In order to make the research more accessible for the network of practitioners and policy-makers, the main research findings will be summarised in an alternative format, such as briefing documents and recommendations.

The summary documents may have important benefits to both private and public sectors, including:

1. Law enforcement authorities: the empirical evidence may inform the development of evidence-led drug crime prevention initiatives, where police resources may be allocated effectively contributing to cost-efficient policing of neighbourhoods.
2. Urban planning authorities: the research findings may raise awareness among urban planners regarding the geographical preferences of offenders engaged in

[1] This part of the research is funded by UCL Advances

drug crime and provide valuable evidence for long term resource allocation and strategic planning of the cities.

3. Consultancy companies involved in providing solutions to businesses regarding security, healthcare, education and urban design.

The research findings will be tailored differently to two main non-academic groups, particularly:

- Crime briefs will be developed for the police, detailing the main research findings, and introducing quantitative and novel mapping methods used to analyse crime. It is disseminated online through security and crime oriented knowledge portals, such as JDiBrief and Polka (hosted by the College of Policing).
- The design recommendations will be presented for an audience of urban planners and policy practitioners for the safer design of schools, hospitals and public spaces. The document also encourages urban practitioners to collaborate more with the police forces when developing policies for new or regeneration areas.

8.5 Limitations of the research

This research has several potential limitations. In Chapter 3 it has already been mentioned that police records are limited only to the detected incidents of drug crime, thus the dataset might not show the complete pattern of all drug crime occurring in the case study area. This is a drawback of any study that uses police data. Additionally, the recorded data are not independent of policing strategy and tactics. Unfortunately, no data were available regarding the spatial distribution of police resources. This type of information could enable cross-checking the geographical distribution of drug crime incidents against police patrols.

Additionally, all the findings are based on the police records from only one case study area with a European style of street network. Although, many findings are consistent with previous research, to establish the external validity of the findings, additional empirical testing of drug crime data is required for different case study areas with both European and non-European styles of street network layouts.

Thus, there are further propositions to be tested in future research.

8.6 Future work

This research informs understanding of the spatial patterning of drug crime and open street drug markets in the city. With these new insights, subsequent research questions have also been developed. The following section highlights the theoretical and methodological implications of the findings for future studies in the disciplines of environmental criminology and urban studies.

One possible future application of the research would be in the anticipation of where drug dealing might be displaced (if it is) following police operations that "close" existing drug markets. Given that drug markets appear to form at very permeable locations, specific predictions can be made as to where it might be most likely to be displaced (Eck 1993). For example, if they are displaced (but see, Weisburd et al., 2006) drug markets may tend to be displaced to the next most permeable locations in an area after police operations. That is, measures of street permeability may be used as predictors of the future locations of drug markets? This could be used to anticipate and hence prevent displacement, were it to occur. Moreover, knowledge of the urban characteristics that contribute to the location of drug markets may help to identify the location of unknown, but existing drug marketplaces.

Another important development would be to examine whether or not there is spatial interaction (dependency) between drug markets and drug related crime. Authors (Goldstein 1985; Bean 2004; Stevens 2005) report that there is a relationship between drug use and crime; that is, that certain types of crime occur as a result of drug influence or as a way to feed drug habits. It would be valuable to look at the spatial patterns of drug-related offences across the street network: do drug-related crimes tend to concentrate near to drug dealing places or on the routes to or from them? Moreover, if a drug market is closed down or displaced how does this affect the drug related crimes?

An analysis of temporal patterns of drug offences, and how such patterns vary along the street network would provide useful insight into the trajectories of drug crime in the city. For instance, it is suggested that such analysis may identify at least two temporal patterns of drug markets: episodic drug markets that appear due to some major event happening in the area, such as summer festivals, and established (chronic or persistent) drug markets that operate throughout the year near the locations that constantly attract large volumes of potential users, such as areas with a recreational night-time economy. In order to test this proposition, a larger dataset than that analysed here would be required. Such a dataset would preferably include at least 5 years of data with information provided on the day and time that drug offences take place.

Finally, the present research used street network distance buffers to estimate the potential *criminogenic field* of facilities. This was defined according to estimates of walking distance that take into account the pattern of street connections. The same three buffer distances were used to model the criminogenic field for all types of facilities. However, it is possible that facilities vary in their spatial catchment area from which they draw potential customers and users. In order to model more precisely the effect from the facility, a weighted street network buffer index can be used. This may involve other factors that contribute to the attractiveness of the facility, such as the size of the land use, the quantity of other facilities nearby, the accessibility to public transport, the profile group of potential users and the size of the residential area (in terms of inhabitants) surrounding the facility. These factors may considerably improve the buffer selection, both theoretically and methodologically.

Finally, with respect to the variation in how some facilities influence the occurrence of drug crime, further research might consider who it is that exerts social control over particular environments. The spatial features of particular facilities and the way people's routine activities are centered around them may create opportunities for drug crime. For example, ambient guardianship may be less effective or more limited near to these semi-public spaces, since those present may perceive that guardianship is the responsibility of the owner of a place. Eck (1994) argues that the way the facilities are managed, mainly the degree of control applied by the owner over the place has a direct effect on the level of crime at the facility, but also in the immediate vicinity. Hence, further research might look at the mechanisms through which place management impacts upon crime, how it might be tailored to reduce its likelihood, and the distance over which different place management strategies might impact upon (drug) crime.

Conclusion

The present research examined the spatial pattern of drug offences with respect to three interrelated features of the urban fabric. A multidisciplinary approach was employed to examine the influence on drug crime of the configuration of the street network, movement patterns and land use distribution. The overall picture suggested that the urban fabric, particularly characteristics of street network configuration and the way land uses are distributed across the street network, have a great effect on drug occurrences as it was originally proposed (Eck 1994). It appears that not only does the geography of drug crime display a non-random pattern, but this pattern can be better understood through a joint theoretical approach stemming from the disciplines of architecture and environmental criminology.

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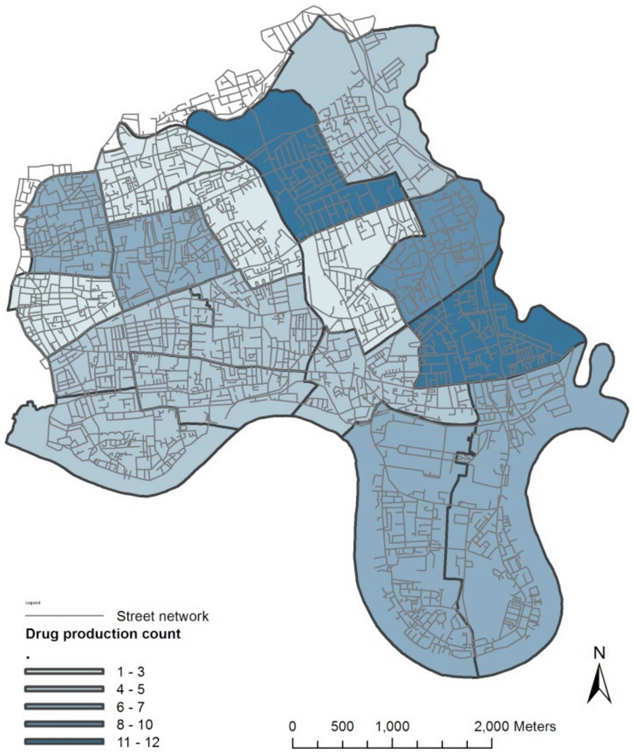
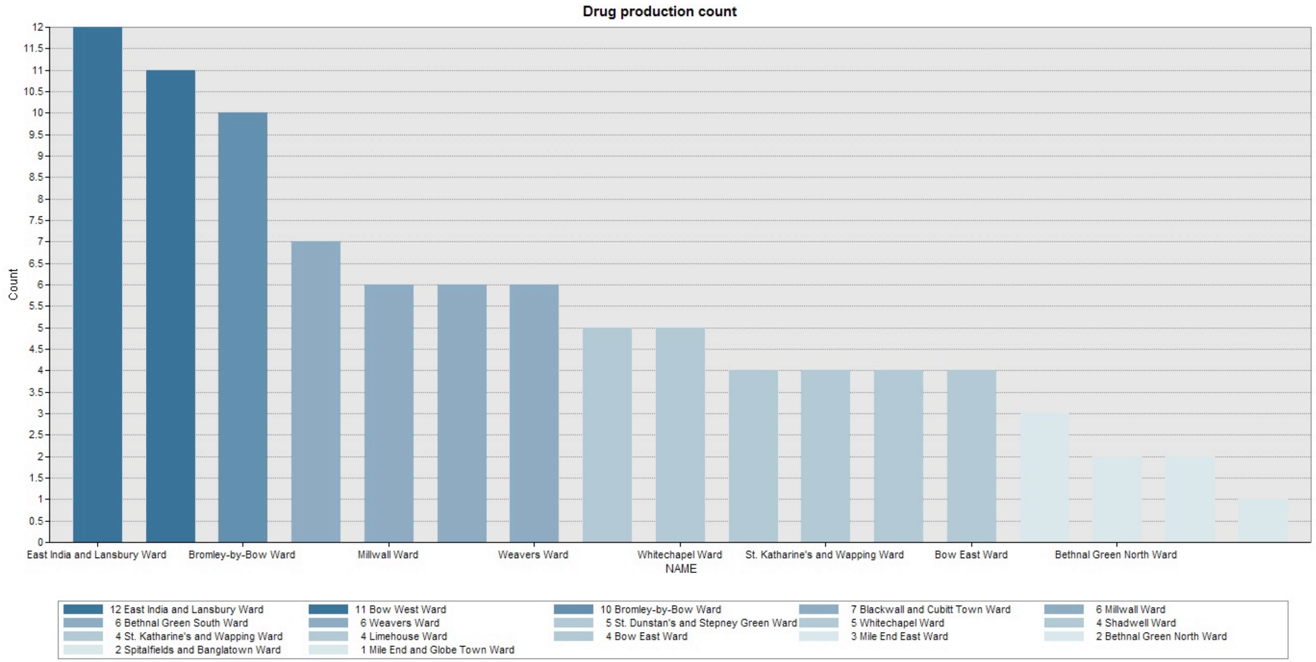
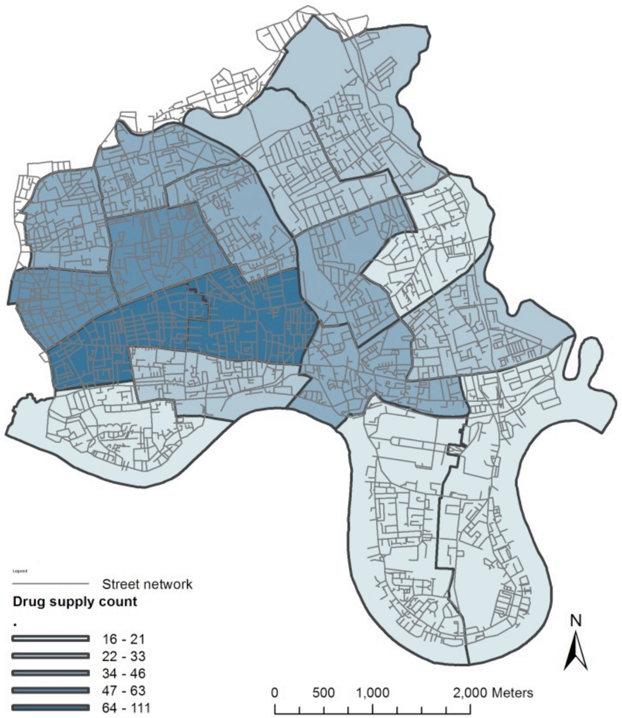
Appendices

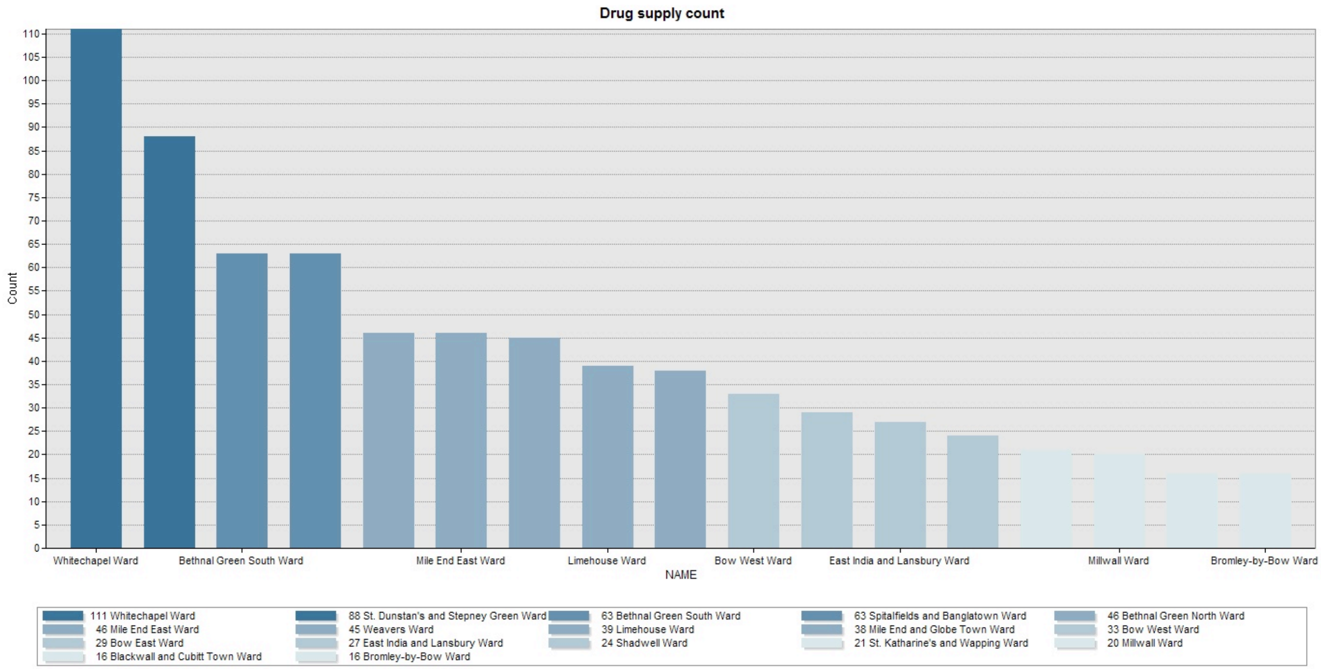
Appendix 1: Aggregate count of drug ***production*** crime (n= 92) in Tower Hamlets grouped according to administrative wards of the borough, the crime count is according to *natural break* distribution.



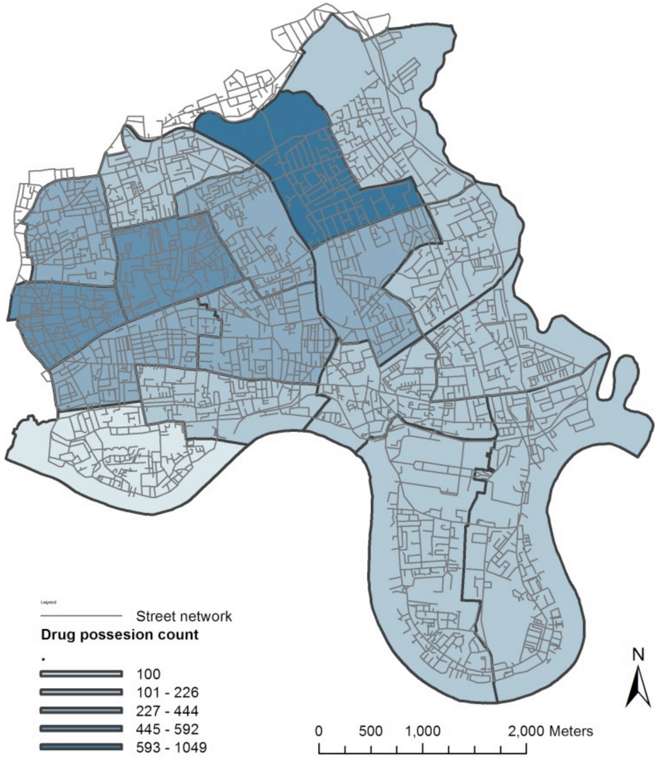


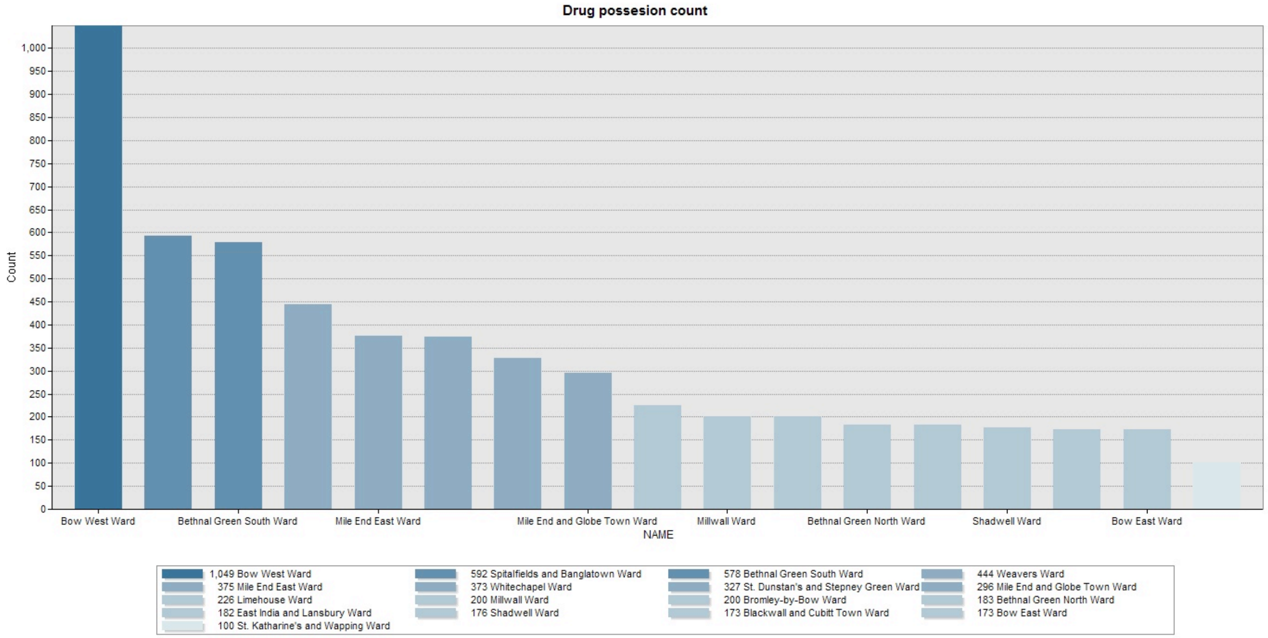
Appendix 2: Aggregate count of drug ***supply*** crime (n=733) in Tower Hamlets grouped according to administrative wards of the borough, the crime count is according to *natural break* distribution.





Appendix 3: Aggregate count of drug ***possession*** crime (n= 5,786) in Tower Hamlets grouped according to administrative wards of the borough, the crime count is according to *natural break* distribution





Appendix 4: Land use frequency in relation to high street expressed as counts, percentage and cumulative percentage

Land use type (n)	**High street**	Land use **count** away from high street			
		2.5min from highstreet	5min from highstreet	10min from highstreet	Elsewhere
Bar	0	116	30	19	20
Cash converter)	0	10	2	2	2
Hospital	0	18	2	1	0
Tube station	0	10	2	3	9
School	0	32	28	27	8
University/College	0	30	5	1	3

Land use type (n)	**High street**	Land use **count expressed as percentage**			
		2.5min from highstreet	5min from highstreet	10min from highstreet	Elsewhere
Bar	0	62.7	16.2	10.2	10.8
Cash converter)	0	62.5	12.5	12.5	12.5
Hospital	0	85.7	9.5	4.7	0
Tube station	0	41.6	8.3	12.5	37.5
School	0	33.6	29.4	28.4	8.4
University/College	0	76.9	12.8	2.5	7.6

Land use type (n)	**High street**	**Cumulative percentage** of land use count			
		2.5min from highstreet	5min from highstreet	10min from highstreet	Elsewhere
Bar	0	62.7	78.9	89.1	100
Cash converter)	0	62.5	75	87.5	100
Hospital	0	85.7	95.2	100	100
Tube station	0	41.6	50	62.5	100
School	0	33.6	63.1	91.5	100
University/College	0	76.9	89.7	92.3	100

Appendix 5: Crime count on segments that are 2.5, 5 and 10 minute walk from/to six land use categories grouped according to 3 drug crime type, (2.5, 5 and 10 minute walking equals to 200m, 400m and 800m distance for London area correspondingly)

Drug crime	Segment with activity node type	Crime **count**			Segment **length (km)**			**Density** of crime		
		Walking distance measured according to time in minutes								
		0-2.5	*2.5-5*	*5-10*	*0-2.5*	*2.5-5*	*5-10*	*0-2.5*	*2.5-5*	*5-10*
Supply	Drinking establishment	302	215	20	133.7	147.8	78.9	2.25	1.45	0.25
	Money lending establishment	36	77	270	11.3	34.1	130.6	3.18	2.25	2.06
	Healthcare use	21	46	215	10.0	23.6	93.2	2.10	1.94	2.30
	Transportation	21	135	364	25.0	61.4	190.1	0.84	2.19	1.91
	Educational use: school	180	201	142	79.5	140.8	133.5	2.26	1.42	1.06
	Educational use: university	81	103	267	29.1	50.6	154.3	2.78	2.03	1.73
Possession	Drinking establishment	2300	1398	292	133.7	147.8	78.9	17.20	9.45	3.70
	Money lending establishment	208	422	2339	11.3	34.1	130.6	18.40	12.37	17.9
	Healthcare use	141	395	1565	10.0	23.6	93.2	14.10	16.73	16.8
	Transportation	447	829	1858	25.0	61.4	190.1	17.88	13.50	9.77
	Educational use: school	976	2129	883	79.5	140.8	133.5	12.27	15.12	6.61
	Educational use: university	707	463	2004	29.1	50.6	154.3	24.30	9.15	13.00
Production	Drinking establishment	25	36	4	133.7	147.8	78.9	0.18	0.24	0.05
	Money lending establishment	3	8	15	11.3	34.1	130.6	0.26	0.23	0.11
	Healthcare use	2	6	13	10.0	23.6	93.2	0.20	0.25	0.13
	Transportation	6	11	32	25.0	61.4	190.1	0.24	0.17	0.16
	Educational use: school	18	28	14	79.5	140.8	133.5	0.22	0.20	0.10
	Educational use: university	6	5	26	29.1	50.6	154.3	0.20	0.10	0.16